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THESIS

MODELING COGNITIVE AND TACTICAL ASPECTS IN HUNTER-KILLER MISSIONS

by

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December 2006

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MODELING COGNITIVE AND TACTICAL ASPECTS IN HUNTER-KILLER MISSIONS

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LIST OF ABBREVIATIONS AND ACRONYMS

ATGM	Anti-Tank Guided Missile
BDA	Battle Damage Assessment
EMT	Expected Mission Time
EPP	Fraction of Engagements Performed
HK	Hunter-Killer
ISR	Intelligence, Surveillance and Reconnaissance
KVTP	Fraction of VTs Killed
MAV	Micro Air-Vehicle
MEP	Fraction of Monitions Expended
NDM	Naturalistic Decision Making
PGM	Precision Guided Munition
PS	Persistent Shooter
RS	Random Shooter
SAM	Surface to Air Missile
SAR	Synthetic Aperture Radar
TCT	Time-Critical Target
TELAR	Transporter, Erector, Launcher and Radar
TST	Time-Sensitive Target
TU	Time Utilization
UAV	Unmanned Air-Vehicle
UCAV	Unmanned Combat Air-Vehicle

VT	Valuable Target
WT	Worthless Target

LIST OF SYMBOLS

A, B	Target type
b_A	Probability that a killed target of type A emits signs of being killed
C	Cautious firing tactic
$c_A^K(n)$	Probability of engaging a target of type A after n engagements
γ	Firing threshold for γ-firing policy
D	Classification Decision Time
δ	A state of perception of a target as dead
E	Time Available for the mission
e	Current Number of Attacked Targets in Mission
F	Decision to acquire the target at the end of a classification
G	Greedy firing tactic
η_A	Expected number of attacks performed by the end of the mission
η_E	Expected number of engagements performed by the end of the mission
η_M	Expected number of munitions expended by the end of the mission
η_{VT}	Expected number of VTs killed by the end of the mission
K	Number of Sites in the Mission
k	Current Number of VTs
$\tilde{k}$	Current Number of Engaged VTs
$\hat{k}$	Current Estimation of k
K_{VT}	Number of VTs in the Mission

$L_Y(n)$	Firing decision rule: the probability of using firing tactic Y after the n^{th} engagement
L_G	Probability of using greedy firing tactic
L_C	Probability of using cautious firing tactic
λ	A state of perception of target as alive
M	Total Number of munitions
$M_A(Y)$	Transition matrix for the classification process, when classifying a target of type A, and using firing tactic Y
μ_A	Mean time to make a decision when classifying a target of type A
μ_D	Expected time of the classification process
μ_F	Expected time of a shot
μ_P	Expected time of preceding preparations for an attack
N	Total Number of Engagements
n	Current Number of Engagements Conducted in Mission
O	Decision to pass over the target at the end of a classification
$P_Y(F \mid A)$	Probability of a decision to acquire a target of type A given firing policy Y
$P_Y(O \mid A)$	Probability of a decision to pass over a target of type A given firing policy Y
$P_A^U(B,m)$	Probability of ending a shooting process with target of type B and m fired munitions, given the target attacked is of type A, and U munitions were allocated
p_A	Single Shot Kill Probability of target of type A
q_∞^A	Limiting probability of correct classification decision when classifying a target of type A
R	Shooting Process Time

S	Classification Process Time
σ_A	Standard deviation of the decision time when classifying a target of type A
T	Classification Window
T_{ref}	Reference Time for the Classification Window
t_A^*	Time in which classification decision quality is no longer significantly improved with time (~60% of the possible improvement has been achieved)
U	Number of Munitions Allocated for an Attack
VT	Target of type VT
$\widehat{VT}$	Classifying a target as VT
WT	Target of type WT
$\widehat{WT}$	Classifying a target as WT
Y	Firing Policy

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GLOSSARY

Anti-Tank Guided Missile (ATGM): A PGM with warhead designed to penetrate armored vehicles. ATGM can be operated from either the surface or from the air.

Battle Damage assessment (BDA): *"The estimate of damage resulting from the application of lethal or nonlethal military force"* [42].

Hunter-Killer (HK): A weapon system, which carries integrated sensors and lethal weapon system, and is capable of acquiring a target and attacking it, independently of other systems.

Precision Guided Munition (PGM): A lethal weapon which uses sensor and navigation system to acquire a target and to hit it with high probability. The guidance can be autonomous or human-piloted. Adopted from [42].

Stand-off Weapon: A weapon which is fired in a large distance away of the target, such that there is no high threat to the shooting platform.

Time-Critical Targets (TCT): Those targets requiring immediate engagement because they pose (or will soon pose) a significant danger to friendly forces. Adopted from [6].

Time-Sensitive Targets (TST): *"Those targets requiring immediate response because they pose (or will soon pose) danger to friendly forces or are highly lucrative, fleeting targets of opportunity"* [42].

Transporter, Erector, Launcher and Radar (TELAR): A vehicle that carries both surface to air missile launcher and radar system—a full system which can intercept air vehicles autonomously of other weapon systems.

Unmanned Combat Air Vehicle (UCAV): A powered, aerial vehicle that does not carry a human operator, and carries a lethal weapon system. Adopted from [42].

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EXECUTIVE SUMMARY

Hunter-Killer weapon systems combine sensors and lethal weapon, and can attack targets without coordination with other weapon systems. These systems are one of the means for dealing with time-sensitive targets. The importance of the capability to deal with time-sensitive, and time-critical targets increases as weapon systems become more mobile and evasive. The targets typical for the recent War on Terror are time-critical in nature.

We consider a mission in which an aerial hunter-killer is sent to classify and attack valuable targets in a set of suspicious target sites, which are detected by other intelligence sources. The operational scenario determines a set of mission parameters, which includes the number of sites and valuable targets, the time available for the mission, and the capabilities of the sensor, the human operator, and the weapon.

When engaging a site, the hunter-killer operator performs a classification process, and decides whether to acquire the target in the site, or to pass over it. If the operator decides to acquire the target, he attacks the target according to a certain shooting tactic.

We are particularly interested in the tactical aspects of the mission planning by the mission planner, and in the cognitive and tactical aspects of the mission execution by the operator of such an aerial hunter-killer.

At the beginning of the mission, the mission planner determines the following parameters:

1. Amount of munitions;
2. Number of engagements to be executed;
3. Length of the classification window, which is the time allocated for classifying the target;
4. Firing policy which guides the operator how to choose a firing tactic: whether to attack or not absent classification (when the target is not classified during the classification window).

These parameters control the expected outcome and duration of the mission.

We model the classification process as a discrete-time Markov chain, in a way that it can utilize data obtained from controlled field experiments. We use this model to explore the effects of skill and speed of performance of the operator under time stress.

We describe two shooting tactics—Persistent and Random—by discrete-time Markov chains. In the Persistent shooting tactic the shooter engages targets sequentially, and during each attack he keeps on shooting at the target, using shoot-look-shoot strategy, until the target emits signs of being killed. The number of shots is limited by the number of munitions allocated for the attack. In this shooting tactics each site is engaged (classified) only once. In the Random shooting tactic the shooter chooses the target randomly on each engagement, and fires at the target only once.

We then combine the classification model and the shooting model into a unified Markov chain model that describes the complete mission for the two cases – Persistent and Random. The Persistent shooter uses a mission support system, which allows him to dynamically adjust the firing policy and the number of munitions allocated for each engagement throughout the mission. The Random Shooter does not have a mission support system and therefore all the engagement parameters are set in advance.

We use the combined model to explore two operational scenarios for a UCAV conducting hunter-killer missions. In the first scenario, a UCAV is sent to destroy a fleeing enemy rocket launcher before it retreats to its hiding place; in the second scenario, a UCAV needs to destroy enemy's surface-to-air battery before a deadline. Through these two scenarios, we demonstrate how the mission planner can enhance the outcome of the mission by adjusting the parameters he controls; and study how different scenario parameters, such as the fraction of targets that are valuable, influence the mission plan and the mission outcomes. We also explore the effect of operator's behavior and shooting tactics on the overall mission performance. We show that different operator archetypes perform well under different mission plans and conditions. Stressful conditions, which may change the operator's behavior and hence capabilities, may degrade the effectiveness of the mission. This observation suggests that a robust mission plan should address also the uncertainty regarding the operator's human factors.

I. INTRODUCTION

A. BACKGROUND

1. Time-Sensitive Targets and Hunter-Killer Systems

Time-sensitive targets (TST) appear in land, air and naval warfare. Examples of TSTs are: tanks in land warfare, ballistic missile launchers in air warfare, and approaching submarines in the sea. Once they pop-up, TSTs require immediate attention and response by the weapons that engage them. As time is critical, coordinating a response of several weapons or military units is a major command and control challenge. One possible approach to cope with TSTs is to use hunter-killer systems (HK), which combine a sensor and a warhead, and can respond to TSTs almost independently of other forces and weapon systems. The simplest example of a hunter-killer weapon is an infantry soldier, who can use his human sensors (eyes and ears) to identify the target, and his personal weapon to kill it. This sensor-weapon combination, which is common and relatively easy to implement in land and naval warfare, mainly because of lesser design constraint, has been a technological challenge in the air. Only recently, significant hunter-killer capabilities were adapted to air vehicles. Although in this research we focus on unmanned aerial hunter-killer systems, the model may be applicable also to other cases of hunter-killer missions.

2. Aerial Hunter-Killer in Modern Air to Ground Warfare

Mobile systems, such as surface to air batteries, ballistic missile launchers and mobile command and control units, are valuable assets in the modern battlefield, and usually available in small quantities. Hence, an attractive way to interdict them is taking the direct approach, destroying them physically, rather than fighting them indirectly to suppress their effectiveness. Locating and attacking this type of mobile time-sensitive target play important parts in air-to-ground operations [1]. The general locations of these targets are usually obtained by cues from theater surveillance sensors, such as satellite imagery, synthetic aperture imaging radars, ground movement indicator radars or signal intelligence sensors. However, these cues, which may give the location of the targets in space and time, may suffer from poor classification and identification capabilities and delays. Thus, to identify and locate TSTs the shooter requires near real-time refinement and tracking, to facilitate an attack by accurate munitions. As these are valuable targets, battle damage assessment (BDA) is essential to verify that a target is killed. This sequential process of dynamic targeting is known as Find, Fix, Track, Target, Engage and Assess, or F2T2EA in short [2]-[7]. Another common term for this target engagement process is the kill chain [2]. The increasing mobility of targets, low availability of cueing opportunities due to camouflage and guerilla tactics, the clutter of a dense battlefield and increasing use of dummies, make this process a tedious, resource consuming effort, during which the attacking assets are not active for a long time and may be sent to attack worthless targets or empty sites [1] and [7].

Recent technological developments enable attacking assets, such as fighter planes and precision guided munitions, to be equipped with intelligence, surveillance and reconnaissance (ISR) sensors, and communication capabilities. This mix of capabilities, which is manifested in unmanned combat air vehicles (UCAVs), such as the US Air Force's MQ-1/MQ-9 Predator A/B [8], and advanced fighter planes equipped with targeting pods, such as LANTIRN, Litening or Sniper [9], allows simplifying and parallelizing the F2T2EA process and increases the rate at which valuable time-sensitive targets are located and attacked [10]. UCAVs and advanced fighter aircrafts can classify and track their targets using their onboard sensors, and subsequently attack these targets. The sensors can also provide BDA on the success of the attack [10]. Thus, a single aerial hunter-killer platform performs all but perhaps the first stage (Find) of the F2T2EA process. The effective combination of weapons and sensors in a single platform may be even more crucial in coping with time-critical targets (TCT) typical in the War on Terror. Targets in this setting may dissolve a short while after detection, as in the case of terrorists in Afghanistan and rocket launchers in Gaza Strip and Lebanon [11].

Compressing the kill chain is a well recognized need [10]. Hunter-killers, and especially UCAVs, are considered as one of the most promising responses to that need [10]. In order to engage a time-sensitive target, the attacker should be able to see it when it is detected, and to attack it without delay. Although each aircraft has limited endurance and payload individually, a force of aerial hunter-killers has no inherent limit on the endurance and munitions available for a specific mission. In theory, a relieving air vehicle (under logistic constraints) can always be sent on time to respond to endurance or munitions shortage (if unexpected failures are ignored). While this fact is true for any aircraft, it is much easier to implement with unmanned air vehicles, thanks to their longer endurance, and the fact that the relief of a vehicle does not affect the operator, which improves the continuity of the mission (if effects of operator's fatigue can be ignored and more than one vehicle can be flown at a time). The time limit on the mission is derived from the expiration time of the cueing intelligence which initiates the mission, and from the fact that in large operations, many missions compete for UCAV resources simultaneously and therefore a mission may be aborted in lieu of another mission. Similarly, the limitation on munitions utilization in a mission is derived from a limited arsenal of accurate munitions, the number of other targets that should be attacked in other "competing" missions, and logistical constraints related to arming many UCAVs with many munitions.

The relatively long endurance of UCAVs, the fact that they can loiter close by to the targets, their high survivability, and the relatively high tolerance to their losses make UCAVs a potentially very effective hunter-killer weapon system for anti-TCT missions [8] and [11]-[15].

Without any onboard sensor, or when operating a stand-off weapon, the only battle damage assessment (BDA) conducted by pilots and operators is an evaluation whether the weapon fired hit the target or missed it, considering a hit as a kill. A possible error in this case is identifying live (surviving) targets as killed [2], [16] and [17]. The sensors on-board UCAVs and the enduring stand-in operation of these platforms allow the operator to perform a more thorough BDA, based on observing positive visual or other indications of a kill. When conducting such visual post attack BDA, the engagement may last longer. In some situations the evidence of a kill following a hit is apparent almost instantaneously because of fire, smoke or sympathetic explosions (See Figure 1 below). If there is no evidence of a kill, the target is considered alive. In this case of post-engagement BDA, a possible error is “false negative”; while live target would never be considered as killed, a killed target may be considered as alive, when no evidence of a kill is present.

Another important potential of UCAVs as hunter-killers is the capability to incorporate advance fire control and operational aid systems, which can easily fit in a ground control unit (GCU), but hardly in a cockpit of an aircraft. By making mission related data available in a user-friendly and intuitive way, advanced mission support systems can help the operator manage the main mission resources—time and munitions—in an efficient way.

Before **After**

Figure 1. Evident Kill of a Hizballah's Multiple Rocket Launcher Captured by Israeli ISR Aerial Asset.
(Source: Israel Defense Force Web Site. Downloaded on 13 August 2006
URL: http://www1.idf.il/SIP_STORAGE/DOVER/files/0/56510.wmv)
Fire and secondary explosions are apparent 3–5 seconds after the vehicle was hit, indicating an assured kill.

There are several known aerial hunter-killer projects, all based on unmanned platform. A few examples are: The RQ-9 Reaper, which is an armed UAV formerly known as "Hunter-Killer" [8], the CUTLASS, suggested by Raytheon [18], Lockheed Martin's Loitering Attack Missile (LAM) [19], and the US Army Confirmatory Hunter-Killer System, which is designated as anti-TCT weapon for urban warfare [20].

B. PROBLEM STATEMENT

1. Balance Resources in HK Missions

We consider a Hunter-Killer (HK) equipped with high-resolution, real time imaging sensor which is used for target classification and BDA, and a weapon system consisting of precision guided munitions. The HK platform may carry additional sensors, which are used for target detection and cueing. We do not consider these capabilities as part of the mission in our problem. We focus on the stages after a set of possible targets' sites has been identified, and the mission is to engage suspicious targets in those sites, as described below. The HK is operated by a human operator, that selects the target sites for engagement, visually classifies the engaged objects and decides whether to acquire it or to pass over it. If the target is acquired, then the HK attacks it, and he may perform a post-attack BDA. The term *engagement* describes a visit to a target site. Each engagement includes the target classification stage. Some engagements include also the attack stage.

We consider a mission in which a single HK is sent to engage time sensitive targets. The operational setting determines the number of target sites, number of valuable targets in those sites and a general time frame for the mission, and the technical setting determines the HK capabilities such as classification accuracy and weapon lethality. The mission planner allocates to the HK munitions, determines the number of engagements to be executed, and sets the classification window, and the firing policy in accordance with the operational constraints and characteristics of the mission. During the mission, the HK operator utilizes these resources and instructions to kill the targets. In this research we explore how to allocate and use the HKs' mission resources (time and munitions) such that the mission is executed effectively and efficiently. Throughout the thesis, we use the terms "hunter-killer" (HK), "operator" and "shooter" interchangeably. We consider two problems associated with the mission:

1. **Planning** the resources allocated to the mission.
2. **Employing** the resources during the execution of the mission.

We focus on the effect of time on the operator's performance, and the possible impact of stress on that performance. We also investigate the effect of memory and mission support systems to the overall performance.

We explore different operational scenarios in terms of time availability, munitions availability and targets density to understand which performance aspects are important and when.

2. The Operational Setting

Typically, attacking air-vehicles are not sent out to search a large area hoping they will find targets to engage. Prior to launching a HK for a combat mission, a detection process is performed by other sensors which provide a set of suspicious sites which may or may not be inhabited by *valuable targets* (VT)—targets that threaten friendly forces or civilians, or have high value for the enemy. VTs are the targets the HK is sent to kill. Because UCAVs cannot compete with real wide area surveillance systems such as JSTARS [21] and satellites, even without prior offline detection, geographical analysis and other basic intelligence techniques reduce the continuous area search problem into a problem of inspecting a finite number of suspicious sites

Consider a HK that is sent on a mission to investigate a set of suspected target sites and to kill valuable targets that are found there. Assume that during the mission, the targets in the sites are stationary, such that a fixed number of sites contain valuable targets, and the rest contain *worthless targets* (WT). WT can be any object that may be in the site and be confused with a valuable target. Depending on the sensors quality and type of targets, WTs may be other military or civilian vehicles, dummy targets or even rocks or bushes. We assume that each site can contain at most one target, either VT or WT. The mission consists of a series of engagements of targets in the various sites. At each engagement, the HK operator picks a site, searches it, and classifies the object in the site as a valuable or worthless target. Then, according to the results of the classification, the HK attacks the target or continues to the next site. If the operator decides to acquire the targets, it is attacked in accordance to a shooting tactic (one shot, shoot-look-shoot, etc.)

Examples for such missions are:

1. Attacking suspected artillery sites, detected by artillery location radar.
2. Attacking forward deployed command posts detected by COMINT sensors.
3. Attacking deployable SAM batteries detected by wide area SAR imagery.

One goal is to maximize the rate at which targets are classified and engaged because prior intelligence regarding the sites may become irrelevant with time, and other missions for the HKs may wait in the pipeline. This goal is attained by minimizing the duration of each engagement. The mission planner controls the duration of the mission by setting a limit on the number of engagements to be performed, and by controlling the length of each engagement. Because the time allocated to each engagement may be limited, the operator is subject to a time constraint on the decision process whether to attack the target in the site or to abandon it. This time limit may affect the probability that the operator classifies the target correctly.

It is also reasonable to assume that the number of munitions allocated for the mission is fixed, so munitions should be utilized efficiently in order to maximize the number of valuable targets killed. In view of the munitions' constraint, another goal is to minimize the number of false-positive classifications, which result in wasted munitions. Because the accuracy of the classification process depends on the time spent on investigating the site, these two goals—minimizing the duration of the engagement and minimizing the number of misclassified targets—are in a conflict.

3. Relevance to Other Operational Scenarios

While our operational setting is UCAV-oriented, it is actually applicable, with some assumptions, to other HK scenarios. The main difference is the fact that many other hunter-killers operate as a group of shooters. Thus, our model is adequate in the case where there is perfect coordination between the shooters; at least subsets of the targets are attacked sequentially; and when survivability issues are not of great concern. Examples for such a mission are attack helicopters attacking mobile targets with anti-tank guided missiles (ATGMs), and a ground unit attacking armor line using ATGMs.

C. LITERATURE REVIEW OF MODELING HK MISSIONS

The emerging role of UAVs in the battlefield, and the wide interest in armed UAVs, and in autonomous loitering munitions, stimulate many research efforts, which are briefly described below.

1. Operator as a Target Classifier

The Army Research Laboratory has a long legacy in developing models for soldier capabilities in target acquisition scenarios [22]. Though most of the models are "engineering models", referring to the soldier as a sensor, some ideas concerning the effects of stress and time on the target-acquisition performance of the soldier are similar to those we use in this thesis.

An Air Force University project [23], which optimizes a coordinated search and classification process of several micro air vehicles (MAV) operated by a single operator, addresses the issue of operator think time, which is similar to our classification time. The think time is modeled by a modified Gamma distribution. The time pressure is captured through queuing of the multiple reports arriving from the MAVs. The cognitive aspects of stress are not addressed in the model, which focuses more on the optimization of the MAV routing. Similar approach of modeling target classification time with Gamma distributions was applied in [24] where friendly and hostile ships are detected and classified under time constraints.

Model for cooperating autonomous HKs in a mission with imperfect classification process was suggested in [25], where the classifications are instantaneous.

2. Shooters with Imperfect BDA

Following an exploration of shooting tactics in the presence of imperfect BDA [26] and [27], we model the HK using a shoot-look-shoot tactic called persistent shooter, in which the attacker attacks a target with a shoot-look-shoot salvo, and never engages this target again. We use a heuristic for optimal munitions allocations developed in [26]. Without time constraints, the greedy shooting tactic, or cyclic shooter who shoots at the perceived line targets in round-robin fashion was proven to be optimal [27]. We do not consider this shooting tactic, as operationally it is difficult to implement and when target acquisition is taken into account, this tactic seems inferior to persistent shooting tactics.

3. HK Mission

Complete models of HK mission are suggested in [25] and [28]. The first model describes a mission of a group of disposable HKs attacking a set of targets, including imperfect classification and BDA. Engagements time is addressed in that model, though target acquisition is modeled as instantaneous.

The second model presents a coordinated/single UCAV search and attack mission. The research focuses more on wide area search with different target distributions, and does not refer to the details of the engagements.

4. Main Contributions of This Thesis

In this research, we expand the models discussed above in the following aspects:

1. Introducing a model for human-operator classification process. The parameters of the model may be estimated from field data.
2. The classification model represents possible behavioral effects of stress in the operator's decision making.
3. The classification model addresses the relations between mission parameters, such as firing policy and limited classification window, and cognitive effects.
4. The Persistent shooting tactic is presented within a complete mission context, while addressing mission uncertainties.
5. The complete mission model addresses engagements of a finite set of target sites rather than search for targets of opportunity in an arbitrary target distribution field.
6. The complete mission model refers to operational planning aspects of the HK mission; these aspects are munitions allocation, time allocation and rules of engagement.

D. STRUCTURE AND METHODOLOGY

We start by modeling the two basic sub-processes of each engagement: the classification process and the shooting process. The classification process model, introduced in Chapter II, represents the cognitive aspects of operator's skills and speed of performance under time pressure. The shooting process model, presented in Chapter III, represents the effects of different shooting tactics based on mission support systems, such as fire control. We consider two shooting tactics. The benchmark tactic is random shooting, which assumes the operator is memory-less and uses no fire-control or mission support system. The second tactic is the Persistent shooter, which uses shoot-look-shoot tactic with limits on munitions consumption. This shooting tactic is used with an advanced mission support system which allows the operator to dynamically adjust tactical mission control parameter to enhance the mission performance. In Chapter IV, we introduce a discrete time Markov chain model that describes the entire mission, based upon the sub-processes developed in Chapters II and III. In Chapter V, we explore different operational scenarios to evaluate the effects of the operator's classification capabilities and shooting tactics, and to determine how the model can be used to improve the resource allocation process done by the mission planner. Concluding remarks and main insights are given in Chapter VI.

II. MODELING THE TARGET CLASSIFICATION PROCESS

In this chapter we present a model for the classification process conducted by a HK operator. First we discuss the operational setting of the process. Then, we introduce a model, which captures cognitive effects of pressure in the time constrained classification process. Based on this model, we introduce a discrete time Markov chain that calculates the probabilities for the outcomes of the process. The chapter concludes with examples of specific operator archetypes.

A. DESCRIPTION OF THE PROCESS

Once the operator detects an object in a site, he attempts to classify it as a VT or a WT. The classification process takes time, and this time is limited to a specified *classification window*, which is determined by operational considerations such as the time criticality of the mission and the endurance of the HK platform. The classification process of a certain object ends if

(a) The operator makes a decision regarding the classification of the object (VT or WT) before the classification window is over.

(b) The classification window is over.

The end result of the classification process is one of the three following events:

1. A decision that the site contains a valuable target (VT).
2. A decision that the site contains a worthless target (WT).
3. The classification window is over and there is no decision

For given operator's capabilities, operational and environmental settings, and classification window, we are interested in specifying the conditional probabilities of these events, given a target of a certain type (VT or WT) is present in the site. In Section C a probability model is developed for the classification process in which we explicitly represent the dependency of these probabilities on the time it takes the operator to classify an object. The parameters of the proposed model can be estimated from data obtained from controlled experiments, as discussed later on.

Clearly, events 1 and 2 follow from termination condition (a), and event 3 follows from termination condition (b). Event 1 results in firing at the target, event 2 results in leaving the current site and traveling to another site, and event 3 may lead to either engaging the target or abandoning it, as discussed next.

1. Firing Policy

In the case of event 3, when the classification window ends before the operator reaches a decision, the operator acts according to a firing policy, which directs him what to do regarding the unclassified target—to engage it or to abandon it. We consider two possible firing tactics: a *greedy tactic* or a *cautious tactic*. The firing policy determines how the operator chooses between these tactics.

<u>Greedy Firing Tactic</u>: According to this tactic, the target is attacked, as there is not enough evidence to reject the assumption that the object is a VT. A firing policy which prefers this tactic will cause more collateral damage and waste of ammunition than a policy which prefers the cautious tactic, but might result in more attacked VTs during the limited duration of the mission. Therefore, this tactic may be preferred in situations when *time* is scarcer than *ammunition*, and there is little penalty for attacking WTs.

<u>Cautious Fire Tactic</u>: According to this tactic, the target is not attacked, as there is not enough evidence to consider it to be a VT. A firing policy which prefers this tactic will reduce collateral damage and waste of ammunition. It might cause more VTs to be ignored during the mission, resulting in wasted opportunities to kill these targets. This tactic may be preferred in situations when *time* is less scarce than *ammunition*.

The choice of the firing tactic is adjusted, according to the battle situation, (in terms of the firing policy) by the mission planner and the operator. It may also be dynamically optimized as a function of the system state.

B. COGNITIVE ASPECTS OF DECISION MAKING UNDER UNCERTAINTY AND TIME CONSTRAINT

The introduction of a classification window makes the classification process one of risk taking decision making made under time pressure.

There are two competing general approaches for modeling the decision making mechanism or cognitive aspects thereof [29]. One approach follows the *Rationalist Paradigms*. In models based on this approach, the decision maker, who has a set of alternatives and an objective, chooses his subjectively optimal alternative according to the objective. Research, however, has shown that a human decision maker is subject to biases, which make his choice of the alternative sub-optimal or wrong [30]. Most of the research on this approach is focused on cognitive and behavioral aspects of judgments and biases of human logic. Issue such as dynamic aspects of the decision, time effects or models for decision mechanism are not captured by the Rationalist approach and therefore it is less appropriate for modeling the dynamic cognitive process of decision making, as in our case.

The second approach is the *Naturalistic Decision Making* (NDM). According to the NDM, the decision maker does not have a structured decision problem in his head, with well-defined objective and complete set of alternatives, but rather uses heuristics, intuition and experience [31 and 32] to decide. The NDM is said to be more realistic than the Rationalist Paradigm for modeling real-time decisions under stress made by experts [29]. The NDM models describe a dynamic cognitive process that imitates real-life decision maker behavior. Unfortunately, no adequate model for target classification under time pressure could be found in the literature. According to Ariely and Zakay in [33], the effect of time constraints on decision making has not been widely reported in the open literature. A similar conclusion is found in [34], which indicates the need for further research.

Bronner [35] states three factors that influence the existence and magnitude of the time pressure effect:

1. **Decision time**: Time limit on the decision process, which the decision maker is aware of and understands the consequences of its violation.
2. **Sensitivity**: The decision maker's cognitive and behavioral sensitivity to time pressure.
3. **Problem Intensity**: The complexity and difficulty associated with the decision problem.

As the decision problem becomes more complex, as the time limit becomes smaller, and as the decision maker's personality is more sensitive to time pressure, the decision is more likely to differ from the one obtained in a more relaxed environment [35].

Dror et al., [36], report that participants in a decision making experiment behaved differently when exposed to time pressure. The participants were playing a Blackjack-like game, and the time for their decision was limited. When experiencing time pressure, their decision regarding low-risk cases were more conservative, i.e., the participants became more hesitant. In high-risk cases, the participants were more daring, i.e., became hastier.

Ariely and Zakay [33] report on a study by Ariely and Amir[1] about the effects of expiring on-line shopping coupons on shopping behavior. They conclude that short-term coupons do not increase the shoppers' propensity to purchase in comparison with non-expiring coupons due to hesitance caused by the perception that a hasty decision may be wrong. Coupons with longer expiration period significantly increased the shoppers' decision rate and their propensity to purchase the product.

Numerous studies regarding the game of chess, e.g., [37] and [38], indicate that players utilize different skills under time pressure. Better players (higher graded masters) are less affected by time stress due to superior skills in "fast mechanisms," such as pattern recognition, according to which they can remember a large set of board states or "patterns" and generate appropriate reactions. Some conclude that the fast mechanism is more likely to explain the differences among high-level players, where skills in slow mechanisms, such as searching through future moves, are about the same [37]. Nevertheless, these studies focus on recognizing the decision mechanisms and their roles and not on rating the players' performance as time pressure increases.

Additional research [34], [39], and [40] shows that time pressure causes changes in the cognitive processes associated with decision making and judgment, and affects the accuracy of the decisions, and the tendency to make them.

[1] On Amir and Dan Ariely, "The effect of expiring coupons on decision making," Technical Report, Massachusetts Institute of Technology, 2000. Report was not published.

Using the insights from these studies, we assert that time constraints affect the operator's classification performance. The effect of the time pressure, or stress, depends on the personality of the operator, on his training, and on the environmental conditions of the mission such as the type of targets, the capabilities of the sensor and the background clutter. When the time is perceived by the operator to be insufficient for performing the classification; the operator may become stressed, which may affect his behavior and his performance. We assume that depending on the operator personality, there is a duration of the classification window, which if he perceives it to be too short, will cause him to become stressed. When that happens, the operator may either get *hasty*, i.e., decide recklessly too fast and make bad decisions or *hesitant*, i.e., tend not to decide during the classification window. The more skillful and experienced the operator, the shorter the classification window that he may endure.

C. PROBABILITY MODEL FOR THE CLASSIFICATION PROCESS

In this section we introduce a probability model which represents the classification process done by an operator. We start with a general behavioral model, and then develop more detailed models that represent the cognitive process of specific operator archetypes. The parameters of the general model can be easily estimated with data obtained from controlled field experiments.

1. The End States of the Classification Process

The classification process terminates in a decision to open fire on the target, or to abandon it. The decision depends on the classification result, if such a result is obtained during the classification window, or on the firing tactic (greedy or cautious) otherwise. Our first model represents the outcomes of the classification process of an object—acquire or pass over—and ignores the cognitive aspects behind it.

Let $P_Y\left(F \mid A,T\right)$ and $P_Y\left(O \mid A,T\right)$ denote the probability of firing at the object, or passing over it, respectively, when engaging a target of type *A* (*A* = *VT* for valuable target, *WT* for worthless target), having classification window of length *T* and applying firing policy *Y (Y* = *C* for cautious, *G* for greedy). For a given classification window *T*, the eight combinations of two firing policies (*C* and *G*), two possible decisions (*F* and *O*), and two target types (*VT* and *WT*) fully probabilistically describe the outcome of the classification process. These probabilities can be estimated directly from observations of controlled field experiments.

We assume a discrete-time model where the classification process is sampled at discrete time steps, starting at time zero. Let *D* =*D(T,Y)* be a discrete random variable, which denotes the time it takes the operator to make a classification decision, given a classification window of length *T*, and firing tactic *Y*. If $D \le T$ then the operator makes a decision (end-state 1 or 2 in Section A above). If *D*>*T* then the target is not classified because the classification window expires (end-state 3 in Section A above).

Define the following events with respect to the operator:

VT : Examining a valuable target (VT).

WT : Examining a worthless target (WT).

$\widehat{VT}$: Classifying a target as valuable.

$\widehat{WT}$: Classifying a target as worthless.

$\Pr\left\{D(T,Y)=t,\hat{A}\,|\,A\right\}$ is the probability that the operator classifies correctly a target of type *A* during the t^{th} time interval of the process, $t \le T$, $\Pr\left\{D(T,Y)=0,\hat{A}\,|\,A\right\}=0$. Similarly, $\Pr\left\{D(T,Y)=t,\hat{A}^C\,|\,A\right\}$ is the probability that the operator classifies incorrectly a target of type *A* during the t^{th} time interval. These probabilities can be estimated by controlled experiments. The probability that the operator, who is classifying a target of type *A*, makes a classification decision during the t^{th} time interval, $t \le T$, is

$$\Pr\left\{D(T,Y)=t\,|\,A\right\}=\Pr\left\{D(T,Y)=t,\hat{A}\,|\,A\right\}+\Pr\left\{D(T,Y)=t,\hat{A}^C\,|\,A\right\}.$$

Let the conditional probability that the operator makes a classification decision during the t^{th} time interval given that a classification decision was not made earlier, when classifying a target of type *A* with classification window *T* and firing tactic *Y* be denoted as

(1) $$d_A^{T,Y}(t) = \frac{\Pr\{D(T,Y)=t \mid A\}}{1-\sum_{\tau=1}^{t-1}\Pr\{D(T,Y)=\tau \mid A\}} .$$

Let the conditional probability of correctly classifying a target of type *A*, given a classification decision was made during the t^{th} time interval be denoted as

(2) $$q_A^{T,Y}(t) = \frac{\Pr\{D(T,Y)=t, \hat{A} \mid A\}}{\Pr\{D(T,Y)=t \mid A\}} .$$

For the sake of simplifying the notation, we omit from now on the superscripts *T* and *Y*.

2. Discrete Markov Chain Model

The key parameters that describe the classification process are the conditional probability of making a decision, $d_A(t)$, and the conditional probability of a correct decision, $q_A(t)$. The classification process is described by the set of transient states t, $0 \le t \le T-1$, the number of time steps since the beginning of the classification process. Another set of states includes the absorbing states, which describe the classification results:

F if the operator decides to fire at the object either because he has classified it as VT or because the classification window is over and the firing tactic is greedy.

O if the operator decides to pass over the object either because he has classified it as WT or because the classification window is over and the firing tactic is cautious.

a. State Transitions

Figure 2 shows the state transition structure of the Markov chain. At each time step there is either a transition to an absorbing (decision) state (*O* or *F*) or to a transient state, which is the next time step. At the last transient step, *T-1*, the only possible transition is to one of the two absorbing states, as the classification window is over.

Assume at first a *cautious* firing tactic. For an engagement of a VT, the following state transitions are possible:

1. $\quad (t) \;\to\; (t+1), \qquad 0 \le t < T-1$

if the classification process is still on at time t+1, with probability $1-d_{VT}(t+1)$.

2. $\quad (t) \;\to\; (F), \qquad 0 \le t \le T-1$

if the target is classified correctly at the t+1 time step, with probability $d_{VT}(t+1)q_{VT}(t+1)$.

3. $\quad (t) \;\to\; (O), \qquad 0 \le t < T-1$

if the target is classified incorrectly at the t+1 time step, with probability $d_{VT}(t+1)(1-q_{VT}(t+1))$.

4. $\quad (T-1) \;\to\; (O)$

if the target is classified incorrectly at the T time step, or no decision is reached during the classification window, with probability $d_{VT}(T)(1-q_{VT}(T))+1-d_{VT}(T)$.

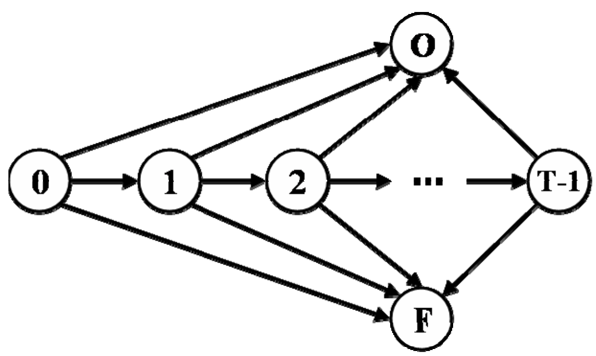

Figure 2. State transition diagram for the classification process as a Markov chain.

The following transition matrix is obtained:

(3) $$\left[\begin{array}{c|c} Q & R \\ \hline 0 & I_2 \end{array}\right] = M_{VT}\left(C\right) \equiv \begin{array}{c|cccccc|cc} & 0 & 1 & 2 & \cdots & T-2 & T-1 & F & O \\ \hline 0 & 0 & 1-d_{VT}(1) & 0 & \cdots & 0 & 0 & d_{VT}(1)q_{VT}(1) & d_{VT}(1)(1-q_{VT}(1)) \\ 1 & 0 & 0 & 1-d_{VT}(2) & \ddots & 0 & 0 & d_{VT}(2)q_{VT}(2) & d_{VT}(2)(1-q_{VT}(2)) \\ 2 & 0 & 0 & 0 & \ddots & 0 & 0 & d_{VT}(3)q_{VT}(3) & d_{VT}(3)(1-q_{VT}(3)) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ T-2 & 0 & 0 & 0 & \cdots & 0 & 1-d_{VT}(T-1) & d_{VT}(T-1)q_{VT}(T-1) & d_{VT}(T-1)(1-q_{VT}(T-1)) \\ T-1 & 0 & 0 & 0 & \cdots & 0 & 0 & d_{VT}(T)q_{VT}(T) & d_{VT}(T)(1-q_{VT}(T))+1-d_{VT}(T) \\ \hline F & 0 & 0 & 0 & \cdots & 0 & 0 & 1 & 0 \\ O & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 1 \end{array}$$

Let R be the sub matrix of M_{VT} (C) which rows correspond to the transient states, and columns to the absorbing states and let Q be the sub matrix of M_{VT}(C), which rows and columns correspond to the transient states, as shown in Equation 3.

The engagement starts at state $t = 0$.

Then, $P_C\left(F \mid VT\right) = \sum_{j=0}^{T-1}\left[\left(I-Q\right)^{-1}\right]_{0j} R_{jF}$.

Notice that $\left[\left(I-Q\right)^{-1}\right]_{0j}$, $j = 0,1,\ldots,T-1$ is the first row of the inverse of a bi-diagonal matrix, where all diagonal entries are equal to 1, and all of the off-diagonal entries are negative. It is easily seen that

$\left[\left(I-Q\right)^{-1}\right]_{0j} = \prod_{t=0}^{j}\left(1-d_{VT}\left(t\right)\right)$, (recall that $d_{VT}\left(0\right)=0$).

$$P_C\left(F \mid VT\right) = \sum_{j=0}^{T-1}\left[\left(I-Q\right)^{-1}\right]_{0j} R_{jF} = \sum_{j=0}^{T-1}\prod_{t=0}^{j}\left(1-d_{VT}\left(t\right)\right)d_{VT}\left(j+1\right)q_{VT}\left(j+1\right)$$

(4) $$P_C\left(O \mid VT\right) = \sum_{j=0}^{T-1}\left[\left(I-Q\right)^{-1}\right]_{0j} R_{jN} = \sum_{j=0}^{T-1}\prod_{t=0}^{j}\left(1-d_{VT}\left(t\right)\right)d_{VT}\left(j+1\right)\left(1-q_{VT}\left(j+1\right)\right)+ \\ +\prod_{t=1}^{T}\left(1-d_{VT}\left(t\right)\right)$$

For the classification of a WT the following state transitions are possible:

1. $\left(t\right) \rightarrow \left(t+1\right), \qquad 0 \le t < T-1$

if the classification process is still on at time t+1, with probability $1-d_{WT}\left(t+1\right)$.

2. $\quad (t) \rightarrow (F), \quad 0 \le t \le T-1$

if the target is classified incorrectly at the t+1 time step, with probability $d_{WT}(t+1)\left(1-q_{WT}(t+1)\right)$.

3. $\quad (t) \rightarrow (O), \quad 0 \le t < T-1$

if the target is classified correctly at the t+1 time step, with probability $d_{WT}(t+1)\,q_{WT}(t+1)$.

4. $\quad (T-1) \rightarrow (O)$

if the target is classified correctly at the T time step, or no decision is reached during the classification window, with probability $d_{WT}(T)\,q_{WT}(T)+1-d_{WT}(T)$.

The following transition matrix is obtained:

$$M_{WT}(C)=\begin{array}{c|cccccc|cc}
 & 0 & 1 & 2 & \cdots & T-2 & T-1 & F & O \\
\hline
0 & 0 & 1-d_{WT}(1) & 0 & \cdots & 0 & 0 & d_{WT}(1)\left(1-q_{WT}(1)\right) & d_{WT}(1)q_{WT}(1) \\
1 & 0 & 0 & 1-d_{WT}(2) & \ddots & 0 & 0 & d_{WT}(2)\left(1-q_{WT}(2)\right) & d_{WT}(2)q_{WT}(2) \\
2 & 0 & 0 & 0 & \ddots & 0 & 0 & d_{WT}(3)\left(1-q_{WT}(3)\right) & d_{WT}(3)q_{WT}(3) \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
T-2 & 0 & 0 & 0 & \cdots & 0 & 1-d_{WT}(T-1) & d_{WT}(T-1)\left(1-q_{WT}(T-1)\right) & d_{WT}(T-1)q_{WT}(T-1) \\
T-1 & 0 & 0 & 0 & \cdots & 0 & 0 & d_{WT}(T)\left(1-q_{WT}(T)\right) & d_{WT}(T)q_{WT}(T)+1-d_{WT}(T) \\
\hline
F & 0 & 0 & 0 & \cdots & 0 & 0 & 1 & 0 \\
O & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 1
\end{array}$$

$$\begin{aligned}
P_C(F\,|\,WT) &= \sum_{j=0}^{T-1}\left[(I-Q)^{-1}\right]_{0j} R_{jF} = \sum_{j=0}^{T-1}\prod_{t=0}^{j}\left(1-d_{WT}(t)\right)d_{WT}(j+1)\left(1-q_{WT}(j+1)\right) \\
P_C(O\,|\,WT) &= \sum_{j=0}^{T-1}\left[(I-Q)^{-1}\right]_{0j} R_{jN} = \sum_{j=0}^{T-1}\prod_{t=0}^{j}\left(1-d_{WT}(t)\right)d_{WT}(j+1)\,q_{WT}(j+1)+ \\
&\qquad + \prod_{t=1}^{T}\left(1-d_{WT}(t)\right)
\end{aligned} \tag{5}$$

Assume now a *greedy* firing tactic. For engagement of a VT, there is a change in the following transitions:

1. $\quad (t) \rightarrow (F), \quad 0 \le t < T-1$

if the target is classified correctly at the t+1 time step, with probability $d_{VT}(t+1)\,q_{VT}(t+1)$.

2. $(t) \;\rightarrow\; (O), \qquad 0 \le t \le T-1$

if the target is classified incorrectly at the t+1 time step, with probability $d_{VT}(t+1)\left(1-q_{VT}(t+1)\right)$.

3. $(T-1), \;\rightarrow\; (F)$

if the target is classified incorrectly at the T time step, or no decision is reached during the classification window, with probability $d_{VT}(T)q_{VT}(T)+1-d_{VT}(T)$.

Thus, the following transition matrix is obtained:

$$M_{VT}(G)=\begin{array}{c|cccccc|cc}
 & 0 & 1 & 2 & \cdots & T-2 & T-1 & F & O \\
\hline
0 & 0 & 1-d_{VT}(1) & 0 & \cdots & 0 & 0 & d_{VT}(1)q_{VT}(1) & d_{VT}(1)\left(1-q_{VT}(1)\right) \\
1 & 0 & 0 & 1-d_{VT}(2) & \ddots & 0 & 0 & d_{VT}(2)q_{VT}(2) & d_{VT}(2)\left(1-q_{VT}(2)\right) \\
2 & 0 & 0 & 0 & \ddots & 0 & 0 & d_{VT}(3)q_{VT}(3) & d_{VT}(3)\left(1-q_{VT}(3)\right) \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
T-2 & 0 & 0 & 0 & \cdots & 0 & 1-d_{VT}(T-1) & d_{VT}(T-1)q_{VT}(T-1) & d_{VT}(T-1)\left(1-q_{VT}(T-1)\right) \\
T-1 & 0 & 0 & 0 & \cdots & 0 & 0 & d_{VT}(T)q_{VT}(T)+1-d_{VT}(T) & d_{VT}(T)\left(1-q_{VT}(T)\right) \\
\hline
F & 0 & 0 & 0 & \cdots & 0 & 0 & 1 & 0 \\
O & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 1
\end{array}$$

$$P_G(F\,|\,VT)=\sum_{j=0}^{T-1}\left[(I-Q)^{-1}\right]_{0j}R_{jF}=\sum_{j=0}^{T-1}\prod_{t=0}^{j}\left(1-d_{VT}(t)\right)d_{VT}(j+1)\,q_{VT}(j+1)+$$

(6) $$+\prod_{t=1}^{T}\left(1-d_{VT}(t)\right)$$

$$P_G(O\,|\,VT)=\sum_{j=0}^{T-1}\left[(I-Q)^{-1}\right]_{0j}R_{jN}=\sum_{j=0}^{T-1}\prod_{t=0}^{j}\left(1-d_{VT}(t)\right)d_{VT}(j+1)\left(1-q_{VT}(j+1)\right)$$

For engagement of a WT, there is a change in the following transitions:

1. $(t) \;\rightarrow\; (F), \qquad 0 \le t < T-1$

if the target is classified incorrectly at the t+1 time step, with probability $d_{WT}(t+1)\left(1-q_{WT}(t+1)\right)$.

2. $(t) \;\rightarrow\; (O), \qquad 0 \le t \le T-1$

if the target is classified correctly at the t+1 time step, with probability $d_{WT}(t+1)\,q_{WT}(t+1)$.

3. $\left(T-1\right) \;\; \rightarrow \;\; \left(F\right)$

if the target is classified incorrectly at the T time step, or no decision was reached during the classification window with probability $d_{WT}\left(T\right)\left(1-q_{WT}\left(T\right)\right)+1-d_{WT}\left(T\right)$.

Thus, the following transition matrix is obtained:

$$M_{WT}\left(G\right)=\begin{array}{c|cccccc|cc}
 & 0 & 1 & 2 & \cdots & T-2 & T-1 & F & O \\ \hline
0 & 0 & 1-d_{WT}(1) & 0 & \cdots & 0 & 0 & d_{WT}(1)\left(1-q_{WT}(1)\right) & d_{WT}(1)q_{WT}(1) \\
1 & 0 & 0 & 1-d_{WT}(2) & \ddots & 0 & 0 & d_{WT}(2)\left(1-q_{WT}(2)\right) & d_{WT}(2)q_{WT}(2) \\
2 & 0 & 0 & 0 & \ddots & 0 & 0 & d_{WT}(3)\left(1-q_{WT}(3)\right) & d_{WT}(3)q_{WT}(3) \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
T-2 & 0 & 0 & 0 & \cdots & 0 & 1-d_{WT}(T-1) & d_{WT}(T-1)\left(1-q_{WT}(T-1)\right) & d_{WT}(T-1)q_{WT}(T-1) \\
T-1 & 0 & 0 & 0 & \cdots & 0 & 0 & d_{WT}(T)\left(1-q_{WT}(T)\right)+1-d_{WT}(T) & d_{WT}(T)q_{WT}(T) \\ \hline
F & 0 & 0 & 0 & \cdots & 0 & 0 & 1 & 0 \\
O & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 1
\end{array}$$

$$P_G\left(F\,|\,WT\right)=\sum_{j=0}^{T-1}\left[\left(I-Q\right)^{-1}\right]_{0j}R_{jF}=\sum_{j=0}^{T-1}\prod_{t=0}^{j}\left(1-d_{WT}\left(t\right)\right)d_{WT}\left(j+1\right)\left(1-q_{WT}\left(j+1\right)\right)+$$

$$+\prod_{t=1}^{T}\left(1-d_{WT}\left(t\right)\right) \tag{7}$$

$$P_G\left(O\,|\,WT\right)=\sum_{j=0}^{T-1}\left[\left(I-Q\right)^{-1}\right]_{0j}R_{jN}=\sum_{j=0}^{T-1}\prod_{t=0}^{j}\left(1-d_{WT}\left(t\right)\right)d_{WT}\left(j+1\right)q_{WT}\left(j+1\right)$$

b. Classification Duration

Let S be the classification process duration. Since the classification process ends either when a decision is made or when the classification window expires, $S=\min\left\{D,T\right\}$. The conditional probability distribution of S given a classification of target of type A is:

$$\Pr\left\{S=t\,|\,A\right\}=\begin{cases}\Pr\left\{D=t\,|\,A\right\}, & \text{if } \; t<T, \\ 1-\sum_{\tau=0}^{T-1}\Pr\left\{D=\tau\,|\,A\right\}, & \text{if } \; t=T, \\ 0, & \text{if } \; t>T.\end{cases}$$

The conditional expected duration of the classification process of target of type A is $E\left[S\,|\,A\right]=\sum_{t=0}^{T-1}t\Pr\left\{D=t\,|\,A\right\}+T\left[1-\sum_{t=0}^{T-1}\Pr\left\{D=t\,|\,A\right\}\right]$.

The conditional expected duration of the classification process of target of type *A* given that a classification decision was made is

$$E\left[S \mid A, D \le T\right] = \frac{\sum_{t=0}^{T} t \Pr\left\{D = t \mid A\right\}}{\sum_{t=0}^{T} \Pr\left\{D = t \mid A\right\}}.$$

The expected duration of the classification process can also be calculated using the transition matrices $M_A(Y)$. The classification ends at the first time step the system enters an absorbing state, thus $S = \min\left(n \ge 1 : X_n \in \{F, O\}\right)$ where X_n is the classification result (an absorbing state). Then, given the system starts at state (0),

$$\text{(8)} \qquad \mu_D(A,T) \equiv E\left[S \mid A\right] = \sum_{j=0}^{T-1} \left(I - Q\right)^{-1}_{0,j} = \sum_{j=1}^{T-1} \prod_{t=0}^{j-1} \left(1 - d_A(t)\right).$$

3. Modeling Operator Archetypes

In order to evaluate the effect of human factors on the overall mission performance, under various operational conditions, we consider two operator attributes: *skill* and *confidence*:

1. **Skill**: How accurate the operator is in classifying an object, and how fast that accuracy can be achieved.
2. **Speed of Performance:** How fast the operator tends to get confident enough to make a classification decision relative to the classification window.

The skill of the operator reflects his training, experience and capabilities, while his speed of performance depends on his personality and self-confidence. We consider two skill levels and three types of operators based on their speed of performance, which result in six operator archetypes. The two skill levels are as follows:

1. **Expert Operator**: an operator whose capability to accurately classify the target requires short time relative to the classification window available in normal operational circumstances, and classifies with high accuracy.
2. **Novice Operator**: an operator who (objectively) needs more time for classification than the Expert, and whose classifications are less accurate than those of the Expert.

The three operator types in terms of speed are as follows:

1. **Balanced Operator**: an operator who is likely to make a classification decision within the classification window, but late enough to utilize time as much as possible to obtain an accurate classification.
2. **Hasty Operator**: an operator who rushes to conclusions, and is overconfident. Thus, he tends to make a classification decision very early within the classification window.
3. **Hesitant Operator**: an operator who is unconfident and tends to postpone his decision longer than needed. Thus he is likely to not make a classification decision by the time the classification window expires.

Hasty and Hesitant operators trade speed with accuracy. When the classification window is unbounded, Hesitant operator always performs better than the Hasty, but when the time is limited, he might not make a decision on time. Hasty operator has shorter classification duration and therefore he always makes a decision within the classification window, but many of these decisions are wrong. Balanced operator has a good balance of accuracy and classification duration to achieve high performance if the classification window is long enough. Sometimes he is too hasty, and decides incorrectly; sometimes he is unconfident, and doesn't make a decision on time; but on average, he makes a decision on time, as accurately as he can, based on his skills.

Any real-world operator may exhibit Balanced, Hasty or Hesitant behavior under different scenarios and conditions of time pressure.

Expert operators operate better than Novice operators with the same speed of performance. Not incorporated directly in the model is the fact that Experts are also more likely to maintain Balanced speed in stressful situations.

We assume the following regarding the operator's classification process:

1. The longer the classification window, the higher the probability of correctly classifying the object because more information regarding the object is available to the operator.
2. As the classification time approaches the limit of the classification window, the probability of a decision increases. Thus the decision rate is increasing towards the end of the classification window. Thus, we assume that the classification duration has increasing-failure-rate distribution.

3. The time spent for classifying a worthless target has higher variance than the time spent for classifying a valuable target. This is due to the large variety of possible worthless targets.

4. In general, it is reasonable to assume that the outcome of the classification process would depend on the firing policy. If the greedy policy is adopted, and the operator is in doubt regarding the type of object in the site, then his decision may be affected by his perception about the effects of type 1 and type 2 errors. For example, if the operator is concerned about collateral damage, he may tend to classify the object as a worthless target, just to avoid engaging it because he knows that no decision will result in an attack. This perception depends on the situation and the personality of the operator, and it is unclear how it is influenced by the firing policy. We believe however that this is a second-order effect and therefore we ignore it in our operator model. Nevertheless, the model we introduced in Section 3 above can capture this dependency.

a. Classification Accuracy

Before any information regarding the object is observed by the operator, the object can be one out of two possibilities: VT or WT. Assuming that the operator does not have information about the entire scenario, such as the number of VTs and WTs, the conditional probability of correct classification, given the target is of either type, is, then, 0.5. This assumption is quite reasonable when the operator perceives his chance to encounter a WT as high enough. As the operator spends more time classifying the target, the operator gains more information about it, and therefore the probability of correct classification increases. It is reasonable to assume that the probability of correct classification decision increases up to a finite limit, q_∞, which is determined by the taget characteristics and the operator's skills.

After a sufficiently long time of observing the target, it is unlikely that the target will present new characteristics, which the operator can observe and base his decision upon. The rate by which the probability of accurately classifying the object approaches the performance limit, q_∞, is govern by the parameter t^*, which represent a time in which most of the information regarding the target is likely to be observed by the operator. The operational settings determine a reference time for the classification window, T_{ref}, which is the average decision time for unconstrained classification of a Balanced operator. It is a natural classification window for the specific type of target and the operator's skill. The value of t^* for each skill level is determines by T_{ref} as shown in Table 2. A classification window with length $T = T_{ref}$ allows high probability of accurate classification before the classification window expires. Imposing a classification window $T < T_{ref}$ limits the probability of correct classification, as per Equation 9, and may induce stress on the operator, such that he changes his behavior and confidence level.

A possible model for the conditional probability of correct classification of a target of type *A* which captures this effect is

$$(9) \qquad Q_A(t) = 0.5 + \left(q_\infty^A - 0.5\right)\left(1 - e^{-t/t_A^*}\right)$$

A similar approach for modeling detection, classification and identification is taken in the “Night Vision Laboratory Search Model” [22].

b. Classification Time

To represent the increasing failure rate of the time of the classification decision (see assumption 2 above) we choose the gamma distribution with shape parameter greater than 1 for the classification time. In addition to having increasing hazard rate, the gamma distribution is relatively easy to manipulate, using a mean and standard deviation.

Let *D* be the decision time; if *D* is less than the classification window length, *T*, then a classification is done at that time and the probability of correct classification is Equation 9 evaluated at time *D*. If $D>T$, then no classification is possible. We first take the time *t* to be a continuous random variable, before discretizing later on in the model.

$$(10) \qquad f_{D|A}(t) = t^{k_A - 1}\frac{e^{-t/\theta_A}}{\theta_A^{\,k_A}\Gamma(k_A)}, \; t \le T$$

Where $k_A > 1$, $k_A = k_A(T)$ and $\theta_A = \theta_A(T)$ are the shape parameter and scale parameter, respectively. We assume that both parameters depend on the classification window *T*.

We can use the method of moments to estimate the two parameters of the gamma distribution. The mean of the gamma distribution is $k_A\theta_A$, and its variance is $k_A\theta_A^2$. Thus, given estimated mean μ and standard deviation σ, the corresponding shape parameter is $k = \frac{\mu^2}{\sigma^2}$, and the scale parameter is $\theta = \frac{\sigma^2}{\mu}$.

c. Summary of Archetypes Modeling

Table 1 presents the four parameters governing the classification process.

Parameter	Description	Affected by
μ_A	Mean time to make a classification decision when classifying a target of type *A*.	operator's skill and speed, target type, sensor ,classification window.
σ_A	Standard deviation of time to classify a target of type *A*.	operator's skill and speed, target type, sensor ,classification window.
q_∞^A	Probability of correct classification of a target given infinite time to decide.	operator's skill , sensor performance, target type.
t_A^*	Time in which decision quality is no longer significantly improved with time (~60% of the possible improvement has been achieved).	operator's skill , sensor performance, target type.

Table 1. Parameters governing the classification model of an operator.

When the classification window, *T*, is changed, the parameters controlling the decision duration, μ and σ, are scaled accordingly. In this way the decision time distribution is adjusted to the classification window. The shorter the classification window the shorter the decision time will be. Shorter classification window degrades the classification performance via two effects:

1. The classification decision will be made sooner, thus it will become less likely to be correct (the parameters controlling the accuracy of the classification, q_∞ and t^*, are not scaled, as they are a function of the operational scenario).
2. Shorter and shorter classification windows will eventually induce stress, which causes a Balanced operator to change his behavior to either Hasty or Hesitant. Operators with these speeds of performance have degraded performance compared to Balanced operator.

d. Parameters for Operator Archetypes

Suppose that the classification window T is adjusted to the mission, such that $T = T_{ref}$. In this case, an operator of any skill has sufficient time to make an accurate classification decision, i.e., Balanced operators exhaust their potential for good classification performance. We characterize the operators by the parameters in Table 2. Following is a short analysis to illustrate how these parameters correctly capture the operator archetypes characteristics.

Speed of Performance	Balanced		Hasty		Hesitant	
Parameter \ Target	VT	WT	VT	WT	VT	WT
μ	$T/2$	$T/2$	$T/8$	$T/8$	T	T
σ	$T/4$	$T/\sqrt{8}$	$T/16$	$T/\sqrt{128}$	$T/2$	$T/\sqrt{2}$
Parameter \ Operator Skill	Expert			Novice		
q_∞	0.9			0.8		
t^*	$T_{ref}/4$			$T_{ref}/2$		

Table 2. Model Parameters for suggested operators.

Figures 3 and 4 show the resulting probability functions for the operator archetypes with the parameters above. *T* is used as the time unit. The figures show how the characteristics of the operator archetypes are captured with the chosen parameters, and what effect has different parameter values on the curves.

The chosen parameters set different classification accuracy functions for the two skill levels (Figure 3). Expert operator reaches accuracy close to its asymptotic capability faster than the Novice operator, whose asymptotic probability is also lower. Both operators get fairly close to the asymptotic probability within one classification window time.

Figure 4 demonstrates the effect of the operator's speed of performance on the probability of making a decision within the classification window. Balanced and Hasty operators are very likely to make a decision on time, while Hesitant operator will make a decision only in about half of the classifications. Hasty operator is very likely to make his classification decision during the first third of the classification window. Balanced operator is more likely to wait and make his decision later, within the last two thirds of the classification window.

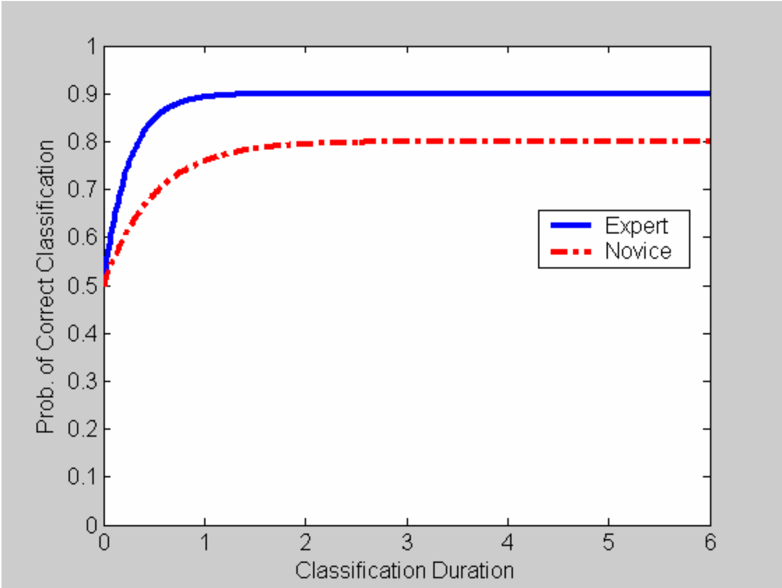

Figure 3. Probability of correct classification for the operators with different skills as a function of classification duration.
The Expert operator has higher probability asymptote and he reaches the asymptote faster than the Novice operator.

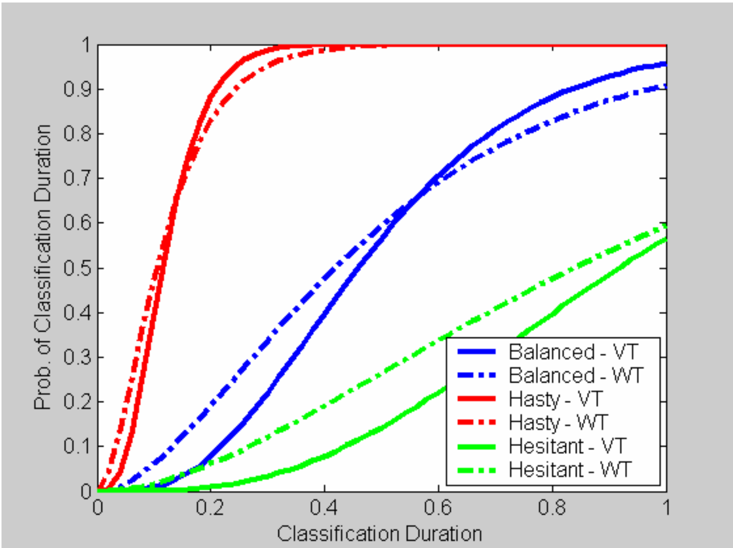

Figure 4. Cumulative probability distribution of the classification duration within a classification window of length 1 for Expert operators with different speeds.
When classifying target of the same type, Hasty operator is always more likely to decide than Balanced operator, and Balanced operator is always more likely to decide than Hesitant operator.

e. Discrete Characterization of the Operator Archetypes

In order to use the operator archetypes described above in the discrete time model that was developed above, we now introduce a discrete version of the probability functions shown above.

Figures 5 and 6 show the discrete probability functions for the operators in the case of classifying valuable target. These probabilities are derived from those shown in Figures 3 and 4.

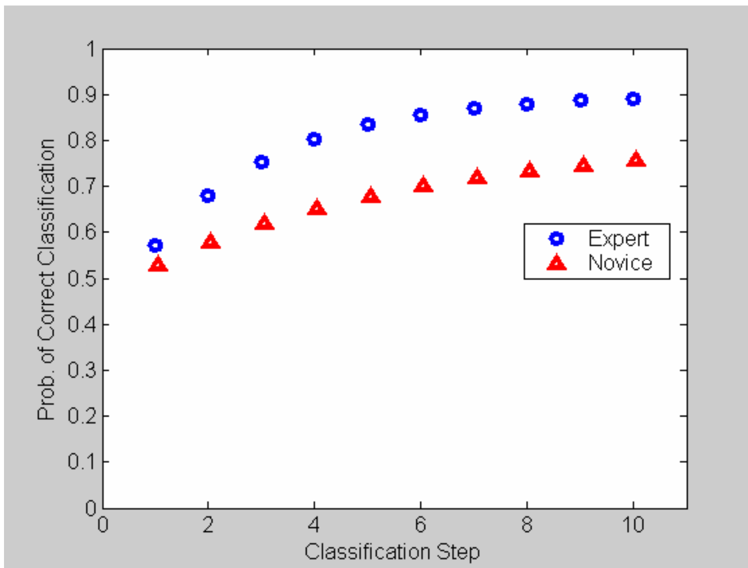

Figure 5. Probability of correct classification, $q_V(t)$, for Expert and Novice operators in 10 time-intervals model (time intervals are of length *T/10*). The probability is approximated by sampling the continuous function at the middle of the time step. This approximation holds if the function is probability of decision is flat enough over one step.

The outcomes of the classification process for each operator are displayed Table 3. Arguably, the Balanced operators have the best performance: for 78% of classifications of valuable targets and 72% of the classifications of worthless targets an Expert Balanced operator will decide to shoot or not to shoot, respectively. A Novice Balanced operator, for comparison, has only 64% and 60% for the same cases.

Notice that when classifying a worthless target, Novice Balanced operator performs very similar to Novice operator with Hasty nature—the difference is in the number of wrong decisions. In both skill levels, Balanced and Hasty operators have more than 50% correct decisions—better than not classifying at all. Hesitant operator has many classifications which end without a decision. Thus, the firing policy will be very dominant in controlling his mission performance. Balanced operators have a small fraction of classifications with no decision. The firing policy will, therefore, have minor effect on their performance. The firing policy will have no effect on Hasty operators, as they practically make a decision in any classification window.

	Target	Valuable			Worthless		
skill	decision / Speed	F	N	NA	F	N	NA
Expert	Balanced	0.78	0.18	0.04	0.19	0.72	0.09
	Hasty	0.65	0.35	0.00	0.34	0.66	0.00
	Hesitant	0.49	0.08	0.43	0.10	0.49	0.41
Novice	Balanced	0.64	0.31	0.04	0.31	0.60	0.09
	Hasty	0.56	0.44	0.00	0.43	0.57	0.00
	Hesitant	0.40	0.16	0.43	0.19	0.41	0.41

Table 3. Classification process outcomes for the suggested operator archetypes.

Table 4 presents the results of operator performance for *neutral* firing policy, which is a policy where a cautious tactic or greedy tactic are adopted with probability 0.5 each for each target for which no classification is made. This firing policy is a baseline, and may be improved when information regarding the operational scenario is available, by changing the probability of adopting each of the firing tactics.

The Balanced operator almost always make a decision, and it is mostly correct, and Hesitant operator makes a decision only in about half of the classifications, but when he makes a decision it is very likely to be correct. Nevertheless, when applying the firing policy, the decisions of the Balanced operator are not much better than the

Hesitant one. The difference between the two is smaller in the Novice skill level case. The performance of Hasty operators is the worst in terms of making the right decision. If a better firing policy is used, this performance gap may get even worse.

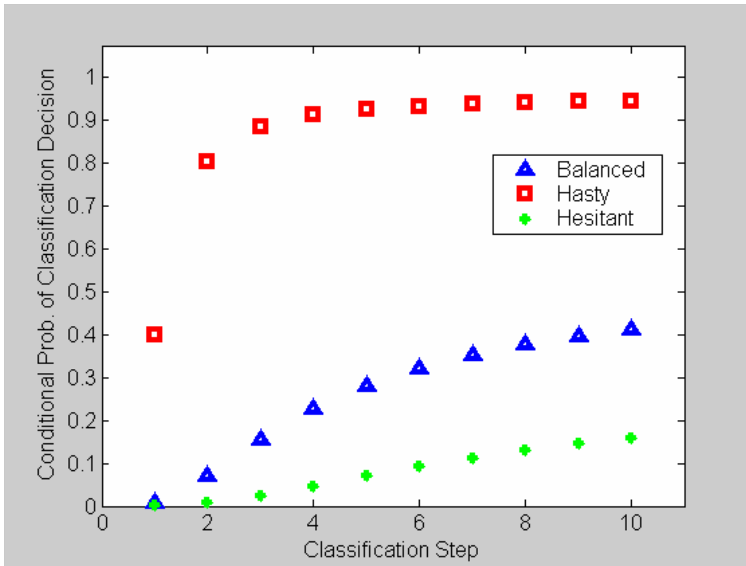

Figure 6. $d_V(t)$ for the suggested operators in ten time-intervals model (time intervals are of length *T/10*).
The discrete probability is calculated by subtraction of the CDF values at the sampled time points.

skill	target \ decision / Speed	Valuable F	Valuable O	Worthless F	Worthless O
Expert	Balanced	0.80	0.20	0.24	0.76
	Hasty	0.65	0.35	0.34	0.66
	Hesitant	0.70	0.30	0.31	0.69
Novice	Balanced	0.67	0.33	0.36	0.64
	Hasty	0.56	0.44	0.43	0.57
	Hesitant	0.62	0.38	0.39	0.61

Table 4. Classification process outcomes when using neutral firing policy for the suggested operator archetypes.

The high performance of the Hesitant operators after including the firing policy rule doesn't come without a price. Hesitant operator will tend to use the entire classification window, and therefore will consume more mission time. Figure 7 displays the distribution of the classification process duration for each operator, and Figure 8 displays the expected values. Hasty operators are expected to use about 20% of the classification window. Balanced operators, either Expert or Novice, are expected to use about 60% of the classification window. Hesitant operators are expected to use 80% of the classification window.

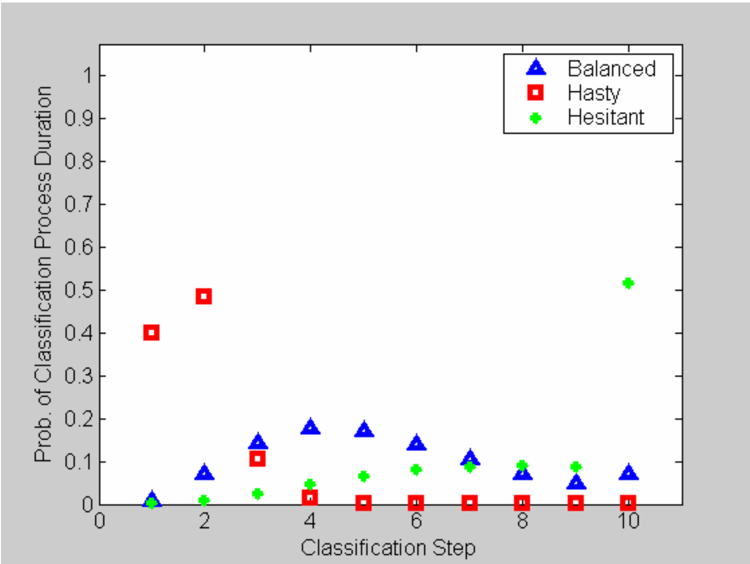

Figure 7. Probability of classification process for the suggested operators in ten time-intervals model (time intervals are of length *T/10*).

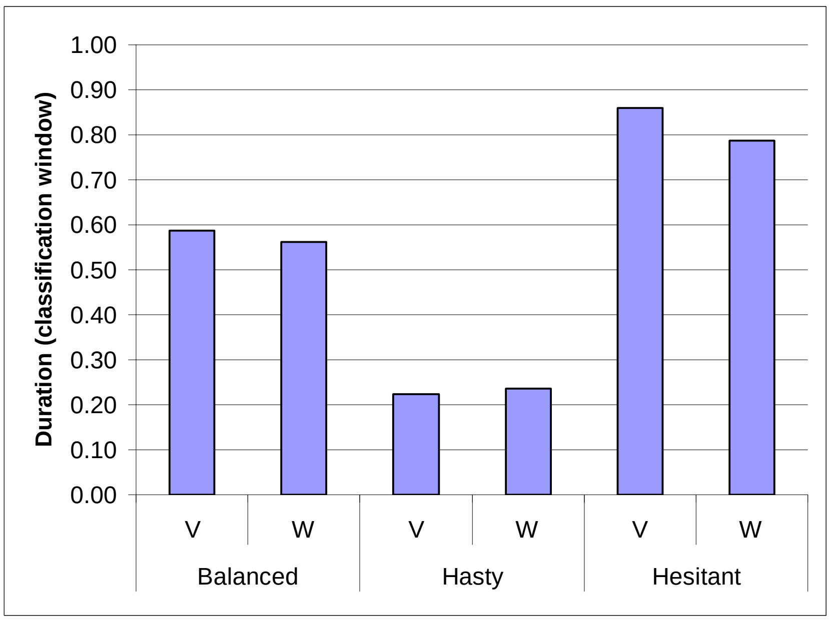

Figure 8. Expected duration of classification process for the suggested operators; the classification window is of length 1.

III. MODELING THE SHOOTING PROCESS

In this chapter, we introduce a model for the shooting process in the engagement. First, we describe the operational setting for the process. We introduce two shooters: *Random Shooter* who has no memory, and no BDA or fire control capabilities, and *Persistent Shooter* who can use shoot-look-shoot tactics and may have mission support and partial BDA capabilities. We develop a discrete time Markov chain model for the shooting process of these two shooters.

A. DESCRIPTION OF THE PROCESS

The shooting process begins once the operator decides to shoot at the object in the site, following the classification process. The shooter may attack the target with a series of shots, after each he may conduct a BDA to verify whether the target is killed or not. If the target is not identified as killed, another shot is fired. This tactic is called *shoot-look-shoot* tactic and it is applied to the Persistent Shooter (see below).

When a worthless target is attacked, there might be no apparent kill at all, as the target may not contain flammable materials or explosives. Nevertheless, we assume that a worthless target, which may be confused with a valuable target, can be affected by a hit in a similar way to a valuable target and emit similar signs when killed.

The nature of the BDA process—in which, after a shot, the shooter looks for positive indication, or evidence, that the target is killed—gives way to errors where a killed target is considered as live. We assume that live targets are not likely to be considered as killed because they are unlikely to emit signs of kill spontaneously.

B. SHOOTING TACTICS AND TYPES OF SHOOTERS

We consider two types of shooters: Random Shooter and Persistent Shooter. The *Random Shooter* fires one shot at the target and leaves the site immediately without conducting BDA. The *Persistent Shooter* conducts shoot-look-shoot tactic using BDA persistently, until the target appears to be *evidently killed*. According to our assumptions, a target that is evidently killed is indeed killed (no false positive errors), but a target that does not appear to be evidently killed may be actually killed (possible false negative errors). The engagement ends either when the target emits signs that indicate it is evidently killed, or when all the munitions allocated to the mission are consumed. An improvement to this tactic is obtained by limiting the number of munitions that can be fired at a target during its engagement. Such a limit may reduce waste of munitions in the case of multi-kills as a result of false BDA [26]. A time-varying limit which takes into consideration the number of munitions left, and the shooter's estimation of the number of future attacks in the mission, can improve the efficiency of munitions' utilization, as discussed later on. The engagement ends when either one of the two following events occurs:

1. The target is evidently killed.
2. All the munitions allocated to the current engagement are consumed.

C. PROBABILITY MODEL FOR THE SHOOTING PROCESS

In this section, we introduce a general Markov process model for the shooting process. This model is applicable for both Random and Persistent shooters.

1. Probability of Kill and Evident Kill

Assume that regardless of whether the attacked target is valuable or worthless, the shooters' performance remains the same for every engagement. Each time the shooter fires at a target of type *A* (*A=VT* for a valuable target, or *WT* for a worthless target), the shot kills it with probability p_A. The shots are independent. Let b_A be the probability that a killed target of type *A* emits signs to that effect after being shot and killed. Then $p_A b_A$ is the probability that an attacked target of type *A* is evidently killed. Recall that absent spontaneous signs of kill, a target can become evidently killed only following a killing shot. Notice also that $b_A = 0$ in the random shooter case.

2. Discrete Markov Chain Model

Let Z denote the perceived state of the target. A target can be in one of two mutually exclusive and exhaustive states of perception throughout the shooting process:

$$Z = \begin{cases} \lambda, & \text{if the target is perceived to be alive,} \\ \delta, & \text{if the target is evidently killed.} \end{cases}$$

Let A denote the type of the target. The target can be either valuable or worthless. VTs become worthless once they are killed. Note that according to our assumption, a VT always appears alive. Figure 9 below presents the possible state transitions in the process.

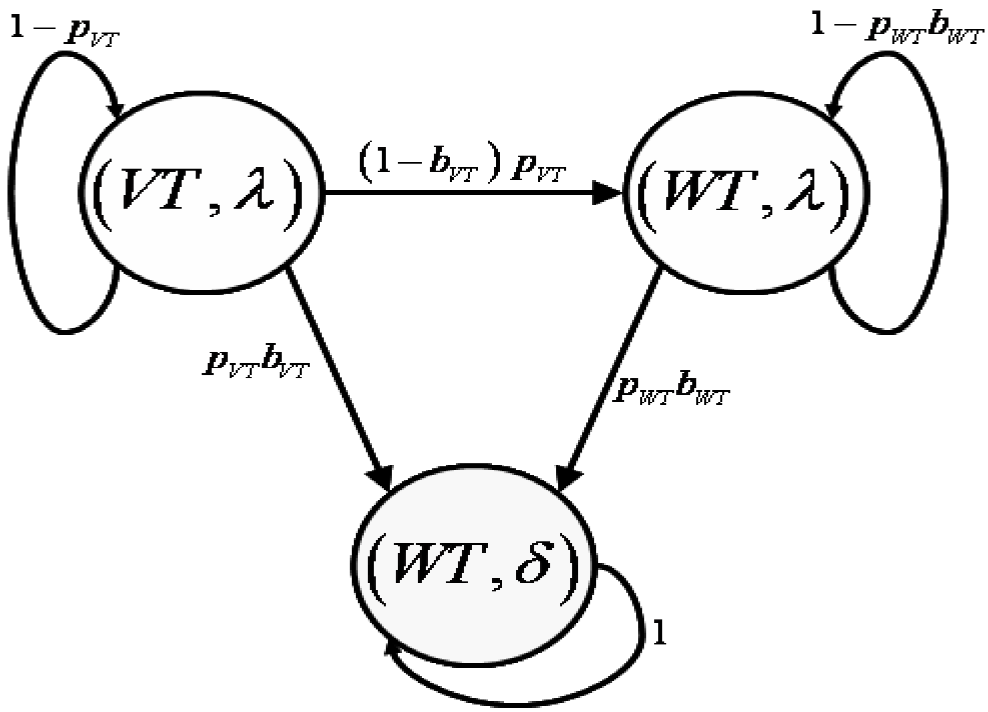

Figure 9. State Transition Diagram for the Shooting Process.

Consider the discrete time process consisting of the states (A,Z). This is a discrete time Markov chain with the following state transitions:

1. $(VT,\lambda) \rightarrow (VT,\lambda)$

if the shot fails to kill the target, with probability $1-p_{VT}$.

2. $(VT,\lambda) \rightarrow (WT,\lambda)$

if the shot kills the target, but it is not evidently killed, with probability $(1-b_{VT})\,p_{VT}$.

3. $(VT,\lambda) \rightarrow (WT,\delta)$

if the shot evidently kills the target, with probability $p_{VT}b_{VT}$.

4. $(WT,\lambda) \rightarrow (WT,\lambda)$

if the shot fails to evidently kill the target, with probability $1-p_{WT}b_{WT}$.

5. $\quad (WT,\lambda) \;\rightarrow\; (WT,\delta)$

if the shot evidently kills the target, with probability $p_{WT}b_{WT}$.

6. $\quad (WT,\delta) \;\rightarrow\; (WT,\delta)$

with probability 1.

Let $P_{i,j}$ denote the entry corresponding to the transition from state *i* to state *j* in the Markov matrix. Then *P* is a 3×3 matrix of the form:

$$P = \begin{array}{c|cc|c} & (VT,\lambda) & (WT,\lambda) & (WT,\delta) \\ \hline (VT,\lambda) & 1-p_{VT} & (1-b_{VT})\,p_{VT} & p_{VT}b_{VT} \\ (WT,\lambda) & 0 & 1-p_{WT}b_{WT} & p_{WT}b_{WT} \\ \hline (WT,\delta) & 0 & 0 & 1 \end{array}$$

Let *U* denote the number of munitions allocated to the current engagement. Each shot corresponds to a time step in the Markov chain. Thus, the engagement has at most *U* time steps.

3. Engagement Results

Based on the Markov chain presented in the previous section, we can calculate the probability distribution of the outcome of a target engagement. Let $P_A^U\left(A',m\right)$ denote the probability that a target of type *A* becomes type *A'* after expending on it *m* munitions, $m \le U$.

$$\begin{aligned} P_{WT}^U\left(WT,m\right) &= \Pr\left\{\text{engagement of a WT ends after } m \text{ shots}\right\} = \\ &= P^{m-1}_{(WT,\lambda),(WT,\lambda)}P_{(WT,\lambda),(WT,\delta)} + P^{m}_{(WT,\lambda),(WT,\lambda)}\delta_{m,U} = \\ &= \left(1-p_{WT}b_{WT}\right)^{m-1}\left(p_{WT}b_{WT}\right) + \left(1-p_{WT}b_{WT}\right)^{U}\delta_{m,U} \end{aligned}$$

$$P_{VT}^U\left(VT,m\right) = \Pr\left\{\begin{matrix}\text{engagement of a VT ends after } m \text{ shots} \\ \text{and the target is alive}\end{matrix}\right\} = \left(1-p_{VT}\right)^{U}\delta_{m,U} \tag{11}$$

$$\begin{aligned} P_{VT}^U\left(WT,m\right) &= \Pr\left\{\begin{matrix}\text{engagement of a VT ends after } m \text{ shots} \\ \text{and the target is killed}\end{matrix}\right\} = \\ &= P^{m-1}_{(VT,\lambda),(VT,\lambda)}P_{(VT,\lambda),(WT,\delta)} + P^{m-1}_{(VT,\lambda),(WT,\lambda)}P_{(WT,\lambda),(WT,\delta)} + \\ &\qquad + P^{U}_{(VT,\lambda),(VT,\lambda)}\delta_{m,U} + P^{U}_{(VT,\lambda),(WT,\lambda)}\delta_{m,U} \end{aligned}$$

where $\delta_{i,j} = \begin{cases} 1, & if\ i = j, \\ 0, & otherwise. \end{cases}$

The Random Shooter fires only one shot during an engagement of a target, and does not perform any BDA. Therefore, there is no shoot-look-shoot process. Hence, the Markov process above is reduced in this shooting process into a very simple case: $m = U = 1$. Therefore, for the Random Shooter:

$$P_{WT}(WT,1) = 1,\ P_{VT}(VT,1) = 1 - p\ ,\ P_{VT}(WT,1) = P_{(VT,\lambda),(WT,\lambda)} + P_{(VT,\lambda),(WT,\delta)} = p\ .$$

D. DURATION OF THE SHOOTING PROCESS

Shooting a munition at a target does not occur instantaneously. First, the shooter gets into a shooting position, which depends on the weapon system and the range to the target. Second, the munition itself travels to the target, which typically takes 20-30 seconds for ATGMs [41]. Finally, a BDA process takes place, if such capability is available. As more munitions are fired during the engagement, its duration becomes longer. Let μ_P denote the expected duration of the preceding preparations for an attack. Such actions may be, for example, a maneuver to allow the release of the weapon. Let μ_F be the expected duration of each shot (including the munition's travel time and the subsequent BDA process). Let *R* be the duration of the shooting process if the shooter decides to attack the target. Assume that the duration of each round of fire is independent of the number of munitions consumed in the engagement. Then the expected duration of a shooting process, given an attack on a target of type *A*, is $E[R \mid A] \equiv \mu_P + \mu_F E[\tilde{m} \mid A]$, where $\tilde{m}$ is the number of munitions fired during the engagement, given that there is a shooting process (i.e., excluding cases where the engagement ends without shooting because of "pass over" decision at the end of the classification process).

For a Random Shooter, each engagement which ends with a shooting process involves only one shot. Thus, the expected duration of the shooting process is $E[R] \equiv \mu_P + \mu_F$.

For a Persistent Shooter, $\tilde{m}$ depends on the number of munitions allocated to the engagement. Since this number may be changed from engagement to engagement, the duration of each attack may have different distribution. The distribution of $\tilde{m}$ given that the attacked target is of type *A* is:

$$\text{(12)} \quad \begin{aligned} &\Pr\{\tilde{m}=m \mid A\} = P_A^U(VT,m) + P_A^U(WT,m) = \\ &= P_{(A,\lambda).(A,\lambda)}^{m-1} P_{(A,\lambda).(W,\delta)} + P_{(A,\lambda).(A^C,\lambda)}^{m-1} P_{(A^C,\lambda).(W,\delta)} + P_{(A,\lambda).(A,\lambda)}^{U} \delta_{m,U} + P_{(A,\lambda).(A^C,\lambda)}^{U} \delta_{m,U} \end{aligned}$$

And the expected value is:

$$\text{(13)} \quad E[\tilde{m} \mid A] = \sum_{m=1}^{U} m\left(P_A^U(VT,m) + P_A^U(WT,m)\right).$$

IV. MODELING THE COMPLETE MISSION

In this chapter, we present the complete model for the hunter-killer mission, which consists of a planning phase and a sequence of engagements. Each engagement includes a classification process and a shooting process. In Section A, we describe the stages of the mission for two types of shooters: the Random shooter and the Persistent shooter. We conclude this section with introducing criteria for measuring the mission performance. In Section B, we develop discrete-time Markov chain models for the multiple-engagement mission, for each type of shooter. For the Persistent shooter we introduce heuristics for adjusting dynamically the firing tactics and the munitions allocation. In Section C, we use the Markov models to calculate specific measures of effectiveness (MOEs). In Section D we present a method for evaluating the expected duration of an engagement.

A. DESCRIPTION OF THE COMPLETE MISSION

1. Introduction: The Mission Structure

The mission consists of two phases: The planning phase and the execution phase. It begins with the planning phase, where the mission planner considers the operational scenario and allocates resources for the mission. The input to this planning is all the scenario related data, including the number of sites, K, the number of valuable targets, K_{VT}, the time, E, and the HK's performance (for more details of these parameters, see Section B6 below). In the planning phase, the mission planner chooses four parameters: the length of the classification window, T, the number of engagements to be executed in the mission, N, the supply of munitions, M, and the shooting policy absent classification (see Section B below). By setting these parameters, the planner controls the expected duration of the mission, and its expected outcome, as will be discussed in details in Section C, and illustrated in Chapter V. Once these parameters are set, the mission enters the execution phase.

The execution phase comprises a series of engagements. Each engagement corresponds to one site. Each site contains one target; the target can be either valuable or worthless. Assuming that the number of VTs, K_{VT}, and the number of sites, K, are known to the HK, the only uncertainty is which sites contain VTs, and which contain WTs. Each engagement consists of the following actions and decisions:

1. Select one of the K sites.
2. Classify the object (target) in the selected site.
3. Decide whether to acquire the target or pass it over, possibly based on the firing policy.
4. Allocate the number of munitions for attacking the target (if acquired). (There is only one type of munition).
5. Shoot at the target (if acquired).

Engagement which contains a shooting process (i.e., the operator decides to acquire the target in the site) is considered as *attack*.

The shooter utilizes the resources allocated for the mission, engagements (N), and munitions (M), and applies the classification window (T) and the firing policy as described in the following paragraphs. The shooter does not consider directly the duration of the mission, but only the duration of each engagement. His mission is to execute the N engagements which are allocated to him by the mission planner.

The mission ends when there are no more munitions left, or when all of the N engagements have been carried out.

2. The Persistent Shooter

The Persistent Shooter (PS) engages the sites sequentially, and when he decides to acquire a target, he applies a shoot-look-shoot tactic, as described in Chapter III. Once he completes engaging a certain target, he never returns to this target's site. Therefore, the Persistent Shooter engages at most N sites, and on each engagement, a site which has not been engaged before, is engaged. We assume that the Persistent Shooter is equipped with an advanced mission support system, which dynamically adjusts the engagement parameters (i.e., firing tactic, and the number of munitions allocation per engagement at a site). Figure 10 presents the mission flow for the Persistent shooter.

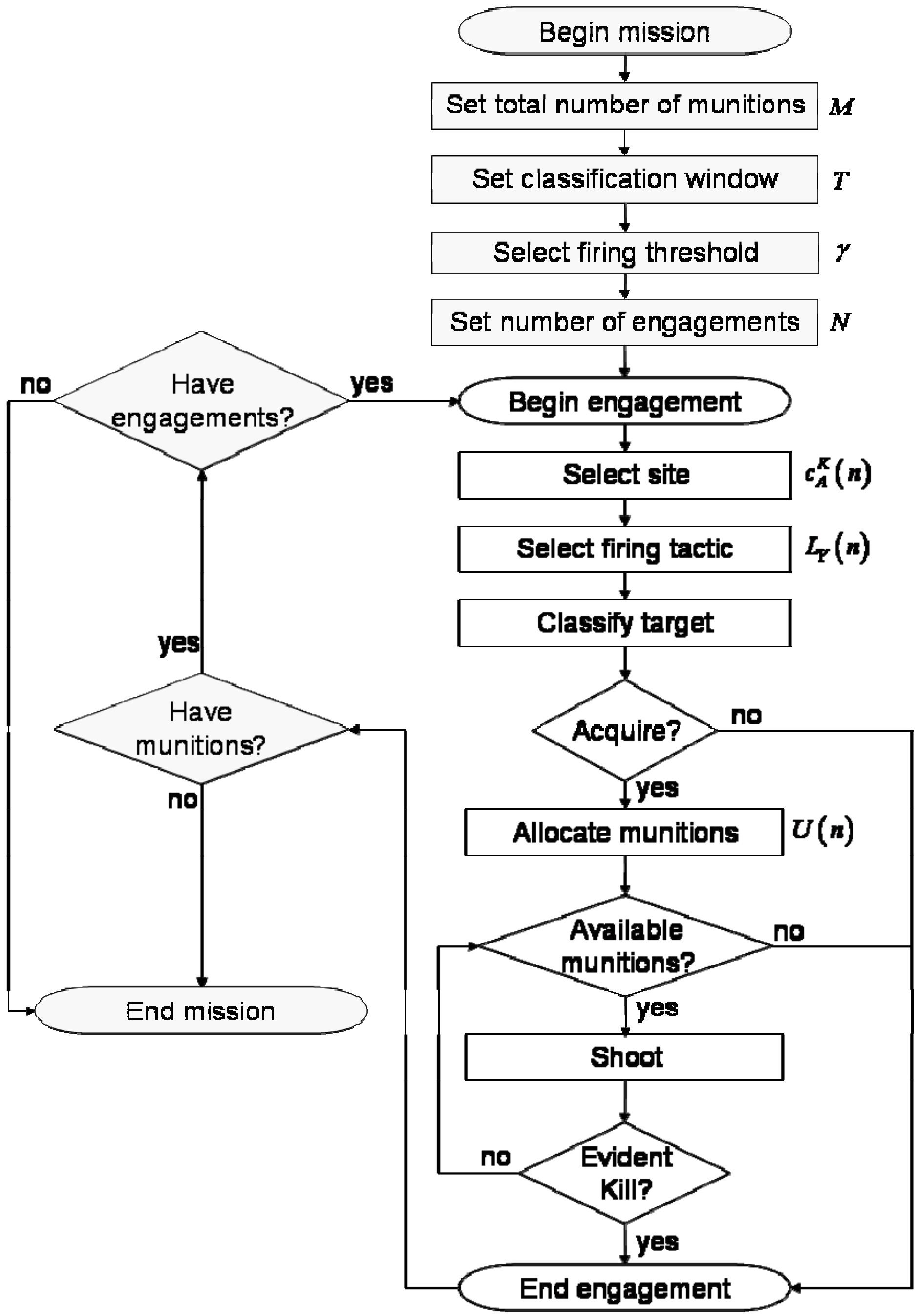

Figure 10. Hunter-Killer Mission Flow Chart for the Persistent Shooter.
The parameters on the right hand side of some boxes refer to sections B1 to B5 below (Equations 14–19).

We assume that the Persistent Shooter, who continuously estimates the number of remaining VTs, will always assume that there is at least one VT remaining. Therefore, the mission will never end because the shooter thinks that there are no more VTs.

3. The Random Shooter

Figure 11 presents the mission flow for the Random Shooter. The Random Shooter (RS) chooses a site at random from the set of site. Then he classifies the object, while using neutral firing policy (chooses at random between greedy and cautious firing tactics) in case no decision is made during the classification window. If the operator decides to acquire the target, he shoots one munition at it. Then, he moves to the next engagement, if he has at least one munition, and at least one engagement left.

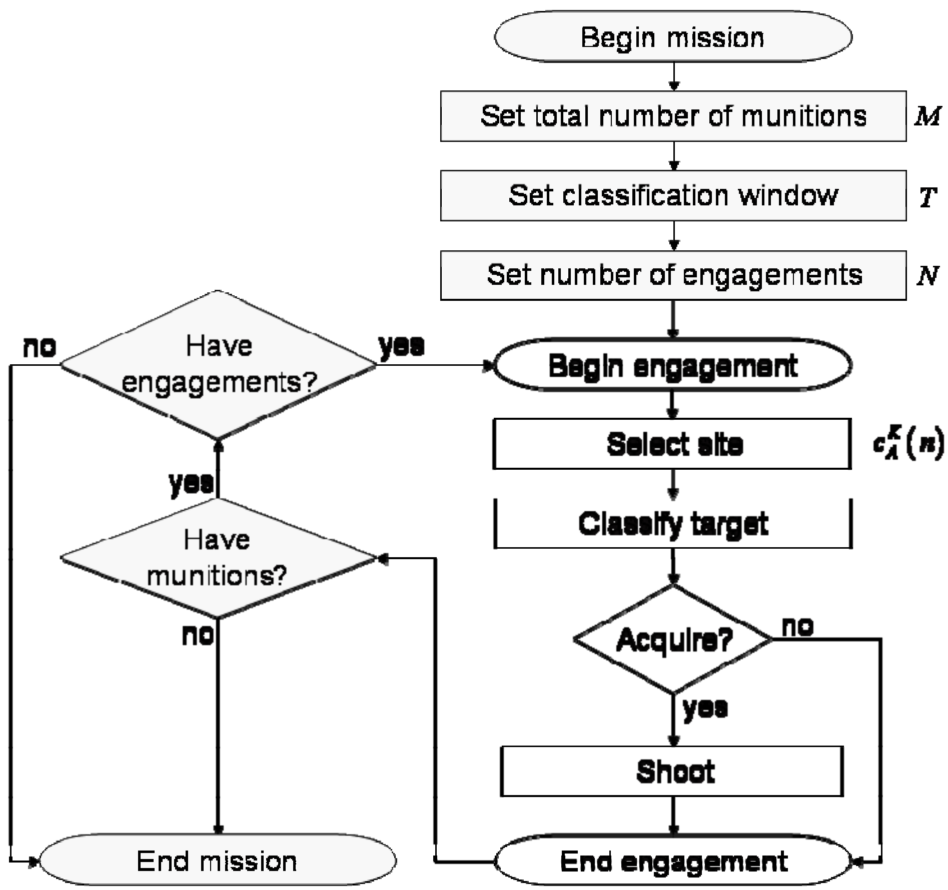

Figure 11. Hunter-Killer Mission Flow Chart for the Random Shooter. The parameters on the right hand side of some boxes refer to sections B1 and B2 below (Equation 15).

4. Criteria for Measures of Effectiveness

The mission can be evaluated by several measures of effectiveness (MOEs), which capture different aspects of an effective mission. In general, there are three criteria according to which the mission is measured:

1. Achieving mission objectives: How many of the VTs are killed?
2. Utilizing weapon effectively and efficiently: How many munitions are fired in total?
3. Using time efficiently: How many of the engagements are performed? How long does the mission last?

The specific MOEs corresponding to these criteria for the models will be defined in Section C of this chapter, using the models which we describe below.

B. INTEGRATED PROBABILITY MODEL FOR THE COMPLETE MISSION

In this section we introduce a probability model that describes the complete mission for the two shooters defined above. We start with definitions and heuristics for calculating the mission parameters, which are the probability of choosing a target of specific type, the firing policy and the munitions allocation for the next engagement. In each paragraph we refer to each of the three shooters. Then we present a discrete-time Markov chain model for each one of the three shooters.

1. Notations

In the following paragraphs we use the notation below:

K Number of sites in the mission.

K_{VT} Number of sites containing valuable targets at the beginning of the mission.

M Number of munitions allocated for the mission.

N Number of engagements allocated for the mission.

T Classification Window

n Current number of engagements completed so far in the mission.

$k(n)$ Number of live VTs at the end of the n^{th} engagement.

$\tilde{k}(n)$ Number of VTs which have been engaged during the first n engagements.

$\hat{k}(n)$ Estimate of $k(n)$ at the end of the n^{th} engagement. This parameter applies only to the Advanced Persistent Shooter.

$e(n)$ Current number of attacks carried out by the end of the n^{th} engagement.

2. Selecting a Site

Let $c_A^K(n)$ be the probability of choosing a site which contains a target of type *A*, *A=VT, or WT,* after *n* engagements, given that there are *K* sites.

a. Persistent Shooter

The Persistent Shooter engages each target at most once. At each engagement, a fresh site is chosen from the list of unengaged sites.

$$(14) \qquad c_A^K(n) = \begin{cases} \frac{K_V - \tilde{k}(n)}{K-n}, & A = V, \\ 1 - \frac{K_V - \tilde{k}(n)}{K-n}, & A = W. \end{cases}$$

b. Random Shooter

At each engagement, the Random Shooter chooses a site at random from the set of *K* sites. The initial number of valuable targets is $k(0) = K_V$.

$$(15) \qquad c_A^K(n) = \begin{cases} \frac{k(n)}{K}, & A = V, \\ 1 - \frac{k(n)}{K}, & A = W. \end{cases}$$

3. Estimating the Current Number of Valuable Targets by the PS

The Random Shooter does not need to estimate the current number of valuable targets after an engagement, as its mission parameters—firing policy and number of allocated munitions—are always fixed and are not updated after an engagement.

Recall that in Section A we assumed that the mission ends only when either the munitions or the engagements are fully exhausted (*m=0* or *n=N*). It does not end even if the operator estimates that there are no more VTs in the area of operations (because he may be wrong). Hence, practically, the operator always behaves as if there is at least one more VT. Therefore the estimator for the number of remaining VTs always satisfies $\hat{k}(n) \geq 1$. Notice that Persistent Shooters will never engage a target more than once, so the outcomes of the previous attacks do not influence his future decisions. This is the essence of the persistent tactics.

At the beginning of each engagement, the Persistent Shooter evaluates the operational situation based on the information that he has so far. An important factor that affects the behavior of the shooter and his decisions is the perceived number of (live) valuable targets after the n^{th} engagement, $\hat{k}(n)$. The number of remaining VTs influences the firing policy and the munitions allocated for the subsequent engagements.

Assume that the number of VTs at the beginning of the mission, K_{VT}, is accurately known to the operator. Also assume that the operator knows the conditional probabilities of acquiring or passing over a target at the end of the classification, $P_Y(F\,|\,A)$, $P_Y(O\,|\,A)$ (see Chapter II). At the end of the n^{th} engagement, let $e(n)$ denote the number of targets he attacked so far. Of those targets/sites he has considered, the number of targets he has not attacked is $n-e(n)$. In order to evaluate how many VTs have been engaged by the end of the n^{th} engagement, the operator uses Bayes' rule to evaluate the probability that an attacked target is a VT, given firing tactic Y,

$$\Pr\{VT\,|\,F\} = \frac{P_Y(F\,|\,VT)\Pr\{VT\}}{P_Y(F\,|\,VT)\Pr\{VT\}+P_Y(F\,|\,WT)\Pr\{WT\}} = \frac{P_Y(F\,|\,VT)\frac{K_{VT}}{K}}{P_Y(F\,|\,VT)\frac{K_{VT}}{K}+P_Y(F\,|\,WT)\left(1-\frac{K_{VT}}{K}\right)}$$

where F indicates the decision to fire at the end of the classification process. Similarly, the probability that a target that was not attacked is a VT is

$$\frac{P_Y(O\,|\,VT)\frac{K_{VT}}{K}}{P_Y(O\,|\,VT)\frac{K_{VT}}{K}+P_Y(O\,|\,WT)\left(1-\frac{K_{VT}}{K}\right)}$$

These probabilities depend on the firing tactics, which may be updated during the mission, according to the firing policy, when moving from one engagement to another. The analysis in Chapter II shows that the firing tactic has no influence on the performance of the Hasty operator and has relatively minor influence on the performance of the Balanced operator. Since the firing policy has low influence on all, but Hesitant operators, we suggest an approximation consisting on a unique firing policy, the neutral policy—a firing policy in which the shooter chooses randomly between greedy firing tactic and cautious firing tactic at each engagement—for estimating $\Pr\{VT\,|\,F\}$. This approximation avoids the need to keep track of the results of previous engagements (which significantly expands the state space), with a small price of inaccuracy. Evidence for the reasonableness of this analysis is shown in the performance measures calculated for different scenarios in Chapter V; ther performance measures show relatively low dependency of the mission performance on the firing policy, especially when the operator is not Hesitant.

Our proposed estimator for the number of remaining VTs is based on the expected number of remaining VTs.

$$
\text{(16)} \qquad \hat{k}(n) = \max\left\{1, \left\lceil \begin{array}{l} K_{VT} - e(n)\frac{K_{VT}}{K}\frac{P_C(F|VT)+P_G(F|VT)}{\left(P_C(F|Vt)+P_G(F|VT)\right)\frac{K_{VT}}{K}+\left(P_C(F|WT)+P_G(F|WT)\right)\left(1-\frac{K_{VT}}{K}\right)} - \\ -\left(n-e(n)\right)\frac{K_{VT}}{K}\frac{P_C(O|VT)+P_G(O|VT)}{\left(P_C(O|VT)+P_G(O|VT)\right)\frac{K_{VT}}{K}+\left(P_C(O|WT)+P_G(O|WT)\right)\left(1-\frac{K_{VT}}{K}\right)} \end{array} \right\rceil \right\}
$$

The estimated number of remaining VTs is the initial number of VTs, K_{VT}, from which we subtract the estimated number of VTs which have been engaged and attacked, and the estimated number of VTs which have been engaged and passed over. Based on our assumption above, this estimate cannot be smaller than 1.

4. Selecting a Firing Tactic

a. Persistent Shooter

It is reasonable to assume that the firing tactics of the PS may be dynamically chosen throughout the mission, based on the perceived performance so far, the known mission parameters, and the firing policy, which is a policy dictated by the planner. The way to choose a firing tactic on each engagement is determined by setting a *firing decision rule*, as will be described below. Intuitively, a *greedy* firing tactic may be appropriate when the battlefield is saturated with valuable targets. A *cautious* firing tactic is more appropriate when there are many worthless targets. How many is considered enough for saturation of VTs or WTs is relative to the tendency to shoot as it being captured by the firing policy. When there is abundance of munitions, or when there is enough time to shoot and classify correctly, the planner may choose firing policy with high tendency to shoot, which will cause the operator of the HK to use more the greedy firing tactic.

The firing decision rule for choosing the fire tactic after the n^{th} engagement can therefore depend on the current perceived density of valuable targets ($\hat{k}(n)/(K-n)$), and on the firing policy. Let the firing decision rule, $L_Y(n)$ be the probability of choosing a firing tactic of type Y (Y=G *or* C) at the end of the n^{th} engagement. In the case where the classification window expires without a decision, the HK attacks the target according to an estimate of the probability that the object is a valuable target, which we denote as $\hat{\mathrm{P}}\left\{VT \mid D > T\right\}$ (see Equation 17 below). The firing policy is chosen by the mission planner to maximize the expected number of killed VTs within the operational constraints of mission resources availability. The γ-firing policy, introduces a *firing threshold*, denoted by $\gamma \in \left[0,1\right]$, to control the value of the firing decision rule. The highest tendency to shoot is represented by $\gamma = 1$. The following heuristic is used to set the firing decision rules: choose greedy firing tactic if the probability that the engaged target is a VT is greater than $1-\gamma$. Thus, a firing threshold of 1 ($\gamma = 1$) means constant greedy firing tactic; a firing threshold of 0 ($\gamma = 0$) means constant cautious firing tactic. As the firing threshold approaches 1, the shooter is more likely to choose a greedy firing tactic, and shoot the target in the case of no classification decision. When a firing tactic of type Y is used constantly (γ is at one of its extremes), we say that a firing policy of type Y is applied.

$$
\begin{aligned}
\hat{\mathrm{P}}\left\{VT \mid D > T\right\} &= \frac{\Pr\left\{D > T \mid VT\right\}\Pr\left\{VT\right\}}{\Pr\left\{D > T \mid VT\right\}\Pr\left\{VT\right\} + \Pr\left\{D > T \mid WT\right\}\Pr\left\{WT\right\}} \simeq \\
&\simeq \frac{\left[P_G\left(F \mid VT\right) - P_C\left(F \mid VT\right)\right]\frac{\hat{k}(n)}{K-n}}{\left[P_G\left(F \mid VT\right) - P_C\left(F \mid VT\right)\right]\frac{\hat{k}(n)}{K-n} + \left[P_G\left(F \mid WT\right) - P_C\left(F \mid WT\right)\right]\left(1 - \frac{\hat{k}(n)}{K-n}\right)}
\end{aligned}
\tag{17}
$$

(See Equations 1-7 in Chapter II)

$$
\begin{aligned}
L_G\left(n\right) &= \begin{cases} 1, & \hat{\mathrm{P}}\left\{VT \mid D > T\right\} \geq 1-\gamma, \\ 0, & \textit{otherwise.} \end{cases} \\
L_C\left(n\right) &= 1 - L_G\left(n\right)
\end{aligned}
\tag{18}
$$

When using this heuristic, $L_Y\left(n\right)$ is a trivial probability function, which gets values of 0 or 1 solely. It means that the operator does not flip a coin to choose a firing tactic. Yet, the firing tactic is chosen according to the estimated probability that the engaged target is a VT.

In Chapter V we will illustrate how the mission planner can use the γ-firing policy to adjust the mission performance according to considerations of mission performance.

b. *Random Shooter*

The Random Shooter is completely memory-less. Hence, the firing policy is random and fixed to be the neutral firing policy—with probability 0.5 he will attack when no decision is made before the classification window expires, that is, $L_G = L_C = 0.5$.

5. Allocating Munitions for Attack by PS

When the classification process ends with a decision to attack the target, the Persistent Shooter determines the number of munitions that will be allocated to that engagement, denoted by *U*. Then, the HK performs the shooting accordingly.

The number of munitions allocated to the engagement, *U*, is dynamically adjusted to maximize the expected number of killed VTs. Aviv and Kress [26] explored several shoot-look-shoot tactics with fire allocation, and demonstrated the effect of limiting the number of munitions for each engagement on the overall outcome of the mission.

The number of munitions allocated to an engagement, *U*, depends on the state of the battle: the number of engagements left in the mission, the available amount of munitions, the estimated number of remaining VTs, and the initial conditions (number of targets and number of valuable targets at the beginning of the mission), which are known to the operator.

Following [26], we consider the following heuristic for allocating munitions for the Persistent Shooter. For each engagement, allocate the munitions equally among all estimated expected future attacks. This heuristic has been shown to be reasonably close to the optimal dynamic program solution in [26], when the exact number of future attacks is known. The operator estimates that there are $\hat{k}(n)$ valuable targets left, and knows that there are $\bar{n} \equiv N - n$ more sites to classify. An estimate for the probability that a site will contain a VT is $\frac{\hat{k}(n)}{K-n}$. Using the fixed neutral firing policy assumption (see Section B3) for calculating the probability of opening fire on VT and WT, the estimated number of future engagements is

$$0.5\frac{\hat{k}(n)}{K-n}\bar{n}\left[P_C\left(F\mid VT\right)+P_G\left(F\mid VT\right)\right]+0.5\left(1-\frac{\hat{k}(n)}{K-n}\right)\bar{n}\left[P_C\left(F\mid WT\right)+P_G\left(F\mid WT\right)\right]$$

Thus, the number of munitions the Persistent Shooter allocates for the engagement after the n^{th} engagement is:

$$U\left(n\right)=\min\left\{m,\left\lceil\frac{2m}{\frac{\hat{k}(n)}{K-n}\bar{n}\left[P_C\left(F|VT\right)+P_G\left(F|VT\right)\right]+\left(1-\frac{\hat{k}(n)}{K-n}\right)\bar{n}\left[P_C\left(F|WT\right)+P_G\left(F|WT\right)\right]}\right\rceil\right\} \tag{19}$$

6. Summary of the Mission Parameters

The operational settings determine the mission data, which includes:

1. The number of sites, K.
2. The number of VTs, K_{VT}.
3. The time, E, available for the mission.
4. The expected time to perform different tasks in the engagements—expected time between engagements, μ_C, expected duration of preceding preparations for an attack, μ_P, expected duration of each shot, μ_F.
5. The reference time for the classification window, T_{ref}. We use this parameter to determine the time-dependence of the classifications accuracy, as described in Chapter II.
6. The operator's performance parameters (See Chapter II).
7. The weapon system performance parameters—the single shot kill probability, p, and the probability that a target emits signs of being killed following a kill, b.

At the planning phase, the mission planner fixes four parameters:

1. The length of the classification window, T.
2. The number of engagements to be executed in the mission, N.
3. The supply of munitions, M.
4. The firing threshold, γ for the γ-firing policy (for PS).

The operator of the Hunter-Killer then performs the mission in accordance with the assigned shooting tactic and mission/planner parameters. The PS determines the number of munitions allocated for each engagement, U, and the probability of using greedy firing tactic. The RS controls no mission parameter.

7. Discrete Time Markov Chain Model for the Complete Mission of the Persistent Shooter

Consider the states given by $\left\{\left(k,m,e,\tilde{k}\right)\right\}$ where k is the total number of remaining VTs (engaged before and not yet engaged), m is the number of remaining munitions for the mission, e is the number of engagements which ended with shooting the target, and $\tilde{k}$ is the number of VTs engaged so far.

Define a discrete-time Markov chain $\left\{X_n, n=0,1,2,\ldots\right\}$, with state space consisting of the states $\left\{\left(k,m,e,\tilde{k}\right)\right\}$, where each step is an engagement. This Markov chain fully describes the battlefield at the end of each engagement and the information the operator needs for future engagements, with $X_0=\left(K_V, M, 0, 0\right)$. The process ends after N engagements or when an absorbing state is reached. The absorbing states are $\left\{\left(k,0,e,\tilde{k}\right)\right\}$—when all the munitions are expended. Figure 12 presents the possible transitions in the Markov chain.

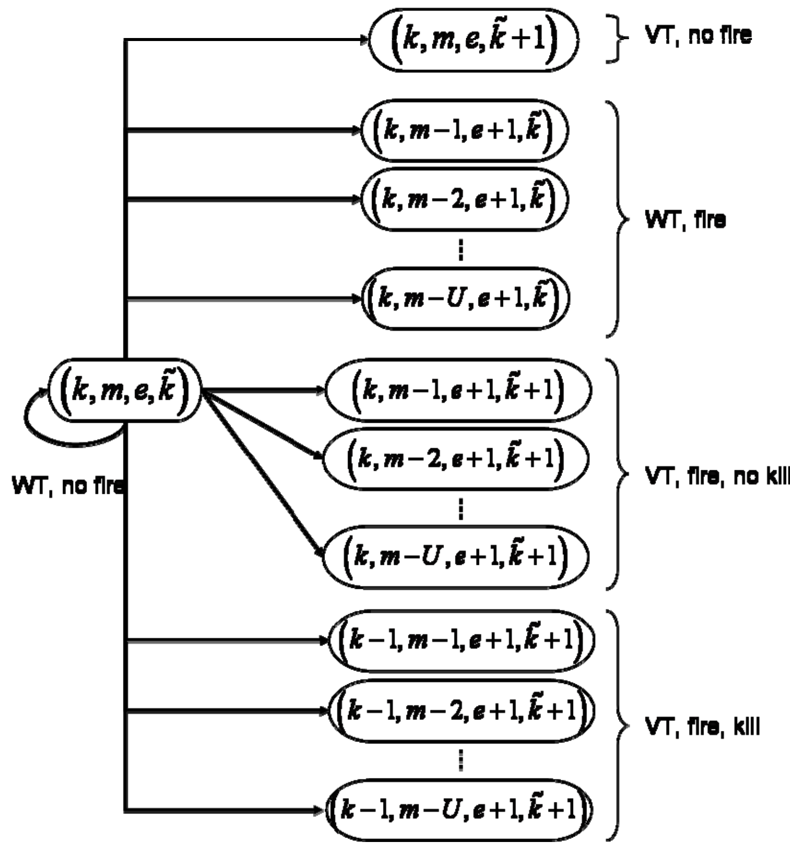

Figure 12. State transitions for the Persistent Shooter Mission.

The state transitions to the $(n+1)^{st}$ engagement are:

1. $(k,m,e,\tilde{k}) \rightarrow (k,m,e,\tilde{k})$

if a WT is engaged, and the classification process ends with a no-fire decision with probability $c_W^K(n)\left[L_G(n)P_G(O|WT)+L_C(n)P_C(O|WT)\right]$, where $c_W^K(n)$, $L_G(n)$, $L_C(n)$ are defined in Sections B1-B4, and $P_G(O|WT)$, $P_C(O|WT)$ are defined in Chapter II.

2. $(k,m,e,\tilde{k}) \rightarrow (k,m,e,\tilde{k}+1)$

if a VT is engaged with a no-fire decision, with probability

$c_V^K(n)\left[L_G(n)P_G(O|VT)+L_C(n)P_C(O|VT)\right]$.

3. $\left(k,m,e,\tilde{k}\right) \rightarrow \left(k,m-\tilde{m},e+1,\tilde{k}\right) \quad 1\le\tilde{m}\le U\left(n\right)$

if a WT is engaged, the classification process ends with a fire decision and the shooting process ends after consuming $\tilde{m}$ munitions with probability $c_W^K\left(n\right)\left[L_G\left(n\right)P_G\left(F\mid WT\right)+L_C\left(n\right)P_C\left(F\mid WT\right)\right]P_{WT}^{U(n)}\left(WT,\tilde{m}\right)$ where U is defined in Section B5, and $P_A^U\left(B,\tilde{m}\right)$ is the probability that a target of type A is attacked with U munitions allocated for the engagement, and the engagement ends when $\tilde{m}$ munitions are fired and the target is of type B, as defined in Chapter III.

4. $\left(k,m,e,\tilde{k}\right) \rightarrow \left(k,m-\tilde{m},e+1,\tilde{k}+1\right) \quad 1\le\tilde{m}\le U\left(n\right)$

if a VT is engaged, the classification process ends with a fire decision and the shooting process ends after consuming $\tilde{m}$ munitions, but the target is still alive with probability $c_V^K\left(n\right)\left[L_G\left(n\right)P_G\left(F\mid VT\right)+L_C\left(n\right)P_C\left(F\mid VT\right)\right]P_{VT}^{U(n)}\left(VT,\tilde{m}\right)$.

5. $\left(k,m,e,\tilde{k}\right) \rightarrow \left(k-1,m-\tilde{m},e+1,\tilde{k}+1\right) \quad 1\le\tilde{m}\le U\left(n\right), k\ge 1$

if a VT is engaged, the classification process ends with a fire decision and the shooting process ends successfully after consuming $\tilde{m}$ munitions with probability $c_V^K\left(n\right)\left[L_G\left(n\right)P_G\left(F\mid VT\right)+L_C\left(n\right)P_C\left(F\mid VT\right)\right]P_{VT}^{U(n)}\left(WT,\tilde{m}\right)$.

6. $\left(k,0,e,\tilde{k}\right) \rightarrow \left(k,0,e,\tilde{k}\right)$

with probability 1

Notice that the transition probabilities may depend on *n*, so this Markov chain does not have stationary transition probabilities.

8. Discrete Time Markov Chain Model for the Complete Mission of the Random Shooter

In this section we present a Markov chain for the Random Shooter. RS has no memory; hence, the behavior of the operator is completely independent of the mission history. Thus, the states of the system can be reduced to $\left(k,m\right)$ where *k* is the number of remaining VTs and *m* is the number of remaining munitions for the mission. Also, there is no dynamic adjustment of policies, so the state transitions are stationary. Figure 13 presents the possible transitions in the Markov chain describing a mission of the Random Shooter.

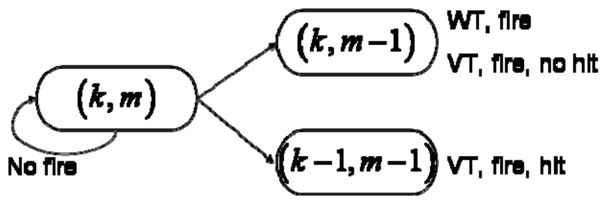

Figure 13. State transitions for the Random Shooter.

The following state transitions are possible:

1. $(k,m) \rightarrow (k,m) \qquad m>0$

if the classification process ends with no no-fire decision, with probability $c_V^K(n)\sum_{Y\in\{C,G\}} L_Y P_Y(O\,|\,VT)+c_W^K(n)\sum_{Y\in\{C,G\}} L_Y P_Y(O\,|\,WT)$.

2. $(k,m) \rightarrow (k,m-1) \qquad m>0$

if a VT is classified correctly but is not killed or a WT is classified incorrectly, and consequently attacked, with probability

$$c_V^K(n)\sum_{Y\in\{C,G\}} L_Y P_Y(F\,|\,VT)(1-p_{VT})+c_W^K(n)\sum_{Y\in\{C,G\}} L_Y P_Y(F\,|\,WT).$$

3. $(k,m) \rightarrow (k-1,m-1) \qquad k,m>0$

if a VT is classified correctly and killed, with probability $c_V^K(n)\sum_{Y\in\{C,G\}} L_Y P_Y(F\,|\,VT)\,p_{VT}$.

4. $(k,0) \rightarrow (k,0)$

with probability 1.

C. DEFINING MEASURES OF EFFECTIVENESS

In this section, we define a set of measures of effectiveness (MOEs), which reflect different aspects of mission success. A successful mission is one that kills the valuable targets, using the given resources of time and munitions. The values of the MOEs may be used to evaluate the outcomes of a planned mission and to adjust its parameters to achieve better results.

We consider four MOEs:

1. The expected fraction of VTs killed (KVTP).
2. The expected fraction of munitions expended (MEP).
3. The expected fraction of engagements performed (EUP).
4. The expected mission time (EMT).

Let

$$x_i = \begin{cases} \left(k_i, m_i\right), & \text{for Random Shooter,} \\ \left(k_i, m_i, e_i, \tilde{k}_i\right), & \text{for Persistent Shooter.} \end{cases}$$

be the state of the system at the end of the i^{th} engagement. The random variables $\left\{x_i\right\}_{i=0}^{N}$ form a Markov chain with transition matrices $\left\{P_i\right\}_{i=1}^{N}$ whose entries are the state transition probabilities calculated above. The initial state is x_0.

Let S denote the number of states in the Markov Chain. P_i is an $S \times S$ matrix. Let

$$v_j = \begin{cases} \left(k_j, m_j\right), & \text{for Random Shooter,} \\ \left(k_j, m_j, e_j, \tilde{k}_j\right), & \text{for Persistent Shooter.} \end{cases}$$

be the j^{th} state in the state space of the mission, $\left\{v_j\right\}_{j=0}^{S}$, such that $x_0 = v_0$ with probability 1. Then the probability that the system is in state u at the end of the mission, after N engagements, given that the system starts at state v_0 is $\Pr\left\{x_N = u\right\} = P_{v_0,u}\left(N\right)$, the v_0, u

entry in the transition matrix $P(N)$, which gives the transition probabilities after N engagements. For the Persistent Shooter $P(N)=\prod_{i=1}^{N} P_i$. For the Random Shooter $P(N)=P^N$.

1. Expected Fraction of VTs Killed

One of the most natural and useful MOEs is the ratio between the number of killed valuable targets and the total number of valuable targets in the area of interest. The expected number of killed VTs at the end of the mission, given that the initial state is v_0 is $\eta_{VT}(v_0)=\sum_{i=1}^{S}(K_V-k_i)P_{v_o,v_i}(N)$, where S is the number of states, k_i is the number of VTs remaining in the i^{th} state and v_i is the i^{th} state. The expected fraction of VTs killed (KVTP) is then $KVTP=\frac{N_{VT}}{K_V}$.

For the Persistent Shooter $\eta_{VT}(v_0)=\sum_{i=1}^{S}(K_V-k_i)\left[\prod_{j=1}^{N} P_j\right]_{v_o,v_i}$ and $v_0=(K_V,M,0,0)$.

For Random Shooter $\eta_{VT}(v_0)=\sum_{i=1}^{S}(K_V-k_i)P_{v_o,v_i}^{N}$ and $v_0=(K_V,M)$.

2. Expected Fraction of Munitions Expended

This MOE is important to measure how restrictive is the allocation of munitions for the mission. If only a small portion of the munitions allocated for the mission is expected to be expended, maybe the unnecessary munitions can be allocated for another mission. If a large portion of the munitions is expected to be fired, maybe allocating more munitions for this mission can significantly improve the performance.

The expected number of munitions fired during the mission given that the system starts at state v_0 is $\eta_M(v_0)=\sum_{i=1}^{S}(M-m_i)P_{v_o,v_i}(N)$. The expected fraction of Munitions Expended is $MEP\equiv\frac{\eta_M}{M}$.

For Persistent Shooter $\eta_M(v_0)=\sum_{i=1}^{S}(M-m_i)\left[\prod_{j=1}^{N} P_j\right]_{v_o,v_i}$ and $v_0=(K_V,M,0,0)$.

For Random Shooter $\eta_M\left(v_0\right)=\sum_{i=1}^{S}\left(M-m_i\right)P_{v_o,v_i}^{N}$ and $v_0=\left(K_V,M\right)$.

3. Expected Fraction of Engagements Performed

Although N engagements are allocated for the mission, the mission may end earlier if all munitions are expended. The expected number of engagements in the mission may be less than N engagements if there aren't enough munitions. It is important to balance the munitions allocation, M, and engagements allocations, N, with the planned duration. The expected number of engagements, given the mission starts at state v_0, is:

$$\eta_E\left(v_0\right)=\sum_{n=1}^{N-1}n\left(\sum_{i\in\{i:m_i=0\}}\sum_{j\notin\{j:m_j=0\}}P_{v_0,v_j}\left(n-1\right)\left[P_j\right]_{v_j,v_i}\right)+N\sum_{j\notin\{j:m_j=0\}}P_{v_0,v_j}\left(N-1\right)$$

The expected fraction of Engagements Performed is: $EPP\equiv\frac{\eta_E}{N}$

For the Persistent Shooter:

$$\eta_E\left(v_0\right)=\sum_{n=1}^{N-1}n\left(\sum_{i\in\{i:m_i=0\}}\sum_{j\notin\{j:m_j=0\}}\left[\prod_{l=1}^{n-1}P_l\right]_{v_o,v_j}\left[P_n\right]_{v_j,v_i}\right)+N\sum_{j\notin\{j:m_j=0\}}\left[\prod_{l=1}^{N-1}P_l\right]_{v_o,v_j}.$$

For the Random Shooter at most one shot is fired in each engagement, thus if $M\geq N$ the mission will always end due to engagements restriction. Otherwise,

$$\eta_E\left(v_0\right)=\sum_{n=1}^{N-1}n\left(\sum_{i\in\{i:m_i=0\}}\sum_{j\notin\{j:m_j=0\}}P_{v_o,v_j}^{n-1}P_{v_j,v_i}\right)+N\sum_{j\notin\{j:m_j=0\}}P_{v_o,v_j}^{N-1}\text{ and }v_0=\left(K_V,M\right).$$

4. Expected Mission Time

In order to make sure that the mission is expected to end on time, the planner considers the expected mission time (*EMT*).

In order to calculate *EMT* the expected number of attacks should be knows. For the PS, the expected number of attacks is given by $\eta_A\left(v_0\right)=\sum_{i=1}^{S}e_i\left[\prod_{j=1}^{N}P_j\right]_{v_o,v_i}$. For RS, the expected number of attacks is equal to the expected number of munitions expended, as on each attack exactly one munition is fired, $\eta_A=\eta_M$. The expected mission time is then:

$$(20) \qquad EMT = (\mu_C + \mu_D)\eta_E + \mu_P\eta_A + \mu_F\eta_M$$

where μ_C is the expected time between engagements, μ_D is the expected time for the classification process (Equation 8), μ_P is the expected time of a preparation for an attack, and μ_F the expected duration of each shot. As the expected mission time approaches the time available for the mission, *E*, it is more likely that the mission will not be accomplished on time.

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V. PERFORMANCE ANALYSIS

A. INTRODUCTION

In this chapter, we study two operational scenarios to demonstrate how the model developed in the previous chapters can be used to analyze real-world Hunter-Killer problems. In each scenario, the operational setting determines the mission data, as described in Section A of Chapter IV. The mission planner creates a *mission plan* by setting the parameters he controls, which are: the number of munitions (M), the classification window (T), the number of engagements (N), and the firing threshold (γ) for the firing policy. The parameters controlled by the shooter depend on its type. On each engagement, the Persistent Shooter controls the number of munitions allocated for the engagement (U), and the firing decision rule (L_G, L_C). The RS does not control any parameters.

In the first scenario, an unmanned combat air vehicle (UCAV) searches the area of operations for a rocket launcher in order to kill it before the launcher retreats to a hiding site. In the second scenario, a UCAV is sent out to attack a surface to air missile (SAM) battery, to clear the way for bombers in a scheduled deep strike operation over the area. Each scenario presents different conditions regarding the mission resources—time and munitions—and the density of valuable targets (K_{VT}/K). In each scenario, we start with a nominal set of parameters describing the mission data, and then vary them in a sensitivity analysis to evaluate how they affect the UCAV's performance. In addition, we examine how the skill and speed of performance of an operator, and his shooting tactics, influence his performance. The measures of effectiveness are: the expected fraction of VTs killed, the expected fraction of munitions expended, the expected fraction of engagements performed, and the expected duration of the mission.

B. SCENARIO A: SHOOT-AND-HIDE ROCKET LAUNCHER

1. Operational Setting

Consider a scenario in which a launch of a medium-range rocket is detected. The launcher is mounted on a pickup truck, which leaves the launch site immediately after the launch, and retreats to a hiding place. An intelligence analysis indicates three potential hiding sites. The analysis also indicates five possible access routes from the launch area to the hiding sites. It is estimated that 3 minutes after the launch, the truck will reach a hiding site. Once reaching a hiding site, the launcher cannot be detected or attacked from the air. A UCAV carrying four munitions is loitering over the launch area. The launch area is an agricultural area in the suburbs of a town. There are a few other vehicles and agricultural equipment used by farmers in the area, which may be confused with the launcher. See Figure 14 for an illustration of the scenario.

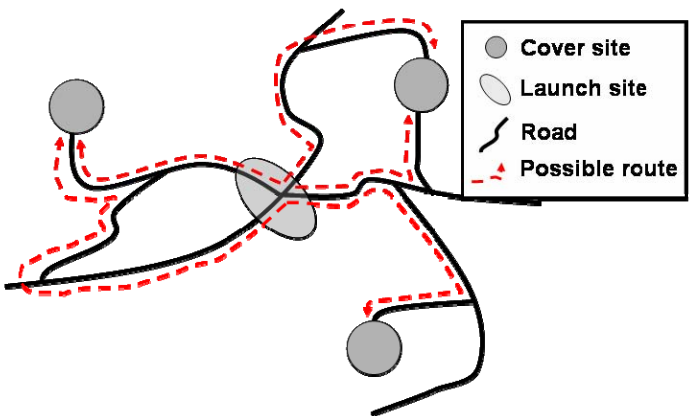

Figure 14. Schematic illustration of scenario A theater.
Each possible route forms a site for classification. The launcher is in one of the sites.

In this scenario, each one of the five access routes is a suspected target site, and might contain the single valuable target—the truck carrying the rocket launcher. During the classification process the operator sweeps through a route, and decides if the object he observes is the launcher or not. Assume that on each route the operator attacks (if he decides to do so) only one object—the one he considers as the launcher (VT). The total expected time available for the mission is three minutes. Assume that this time is too short to coordinate a replacement UCAV to take over the mission, so there are four munitions available to kill the launcher. Table 5 presents the nominal values of the parameters for this scenario. It is assumed the VT is available during the entire mission duration even if it exceeds 3 minutes (yet, the mission planner should make sure that the expected mission time does not exceed 3 minutes).

E	K	K_{VT}	μ_C	T_{Ref}	q_∞	μ_P	μ_F	p	b
3	5	1	0	1	0.9	0.3	0.3	0.8	0.8

Table 5. Nominal Parameters for scenario A.

μ_C—expected time between engagements (see Section C in Chapter IV), μ_P—expected duration of preceding preparations for an attack (see Section D in Chapter III), μ_F—expected duration of each shot (see Section D in Chapter III), T_{ref}—reference classification window for normal operational conditions (see Section C in Chapter II), q_∞—the limiting probability of correct classification for Expert operator (see Section C in Chapter II), p—the single shot kill probability, b—the probability that a target emits signs of being killed following a kill.

In this scenario there is a low density of valuable targets (K_{VT}/K)—only one of the five sites, 20%, contains a valuable target. The time available for the mission (3 min) is very short.

2. Baseline Mission Plan

We start with forming a baseline mission plan, assuming that the operator is a Balanced Expert and he is using the Persistent Shooter tactic. First, the mission planner sets the number of munitions. The operational constraint to use only one UCAV does not allow the mission planner to allocate more than $M=4$ munitions. This number seems to be sufficient, as there is only one VT, only 5 sites, and probably not enough time to shoot all the available munitions, as each shot takes 18 seconds (μ_F) and shooting all of the munitions takes, on average, 72 seconds, leaving less than two minutes for classifications and preceding preparations for attacks (which takes each 18 seconds, on average). As a start, the mission planner sets the classification window to the reference time, $T=T_{ref}=1min$, to avoid stress. Then, the number of engagements, N, is adjusted by trial and error process, such that the expected mission time (*EMT*) does not exceed the time available for the mission, $E=3min$. After fixing M and T, The mission planner sets different values for N and γ, and calculates the consequent *EMT*, until the *KVTP* is maximized subject to the time constraint $EMT \le E$.

When the classification window is set to the reference time, T_{ref} (1min), then four engagements (N = 4) can be carried out such that $EMT \le E$) if a firing policy with low firing threshold γ is used, and three engagements (N = 3) can be carried out on time for a firing policy with high firing threshold (γ approaches to 1). With three engagements, there is a chance of 40% that the target will not be engaged at all, as there are 5 sites to engaged, and the probability that the launcher will be at one of the three which are engaged is 0.6. Table 6 presents MOE values for the mission plan with Balanced Expert PS, and the nominal mission parameters as presented in Table 5, when the classification window is set to one minute, and there are three to four engagements. Each line in Table 6 corresponds to a different firing policy and different number of engagements, as determined by setting the firing threshold, γ and the number of engagement *N*.

MOE / γ , *N*	*KVTP*	*EPP*	*MEP*	*EMT*
0, 3	0.46	0.98	0.34	2.18
0, 4	0.61	0.97	0.44	2.89
0.75, 3	0.46	0.98	0.34	2.18
0.75, 4	0.62	0.97	0.47	2.95
1, 3	0.48	0.97	0.43	2.35

Table 6. MOEs for Scenario A , $T=T_{Ref}=1min$.
γ —*firing threshold*, *KVTP*—fraction of VTs killed, *EPP*—fraction of engagements performed, *MEP*—fraction of munitions expended, *EMT*—expected mission time (minutes).
The expected mission time for $\gamma = 1$ and *N=4* exceeds the available 3 minutes.

When four engagements are allocated, the expected mission time (*EMT*) gets very close to the time available for the mission, 3 minutes, compared with mission with 3 engagements. This fact causes a higher risk that when the mission lasts longer than expected, the launcher may escape.

The probability of killing the launcher equals to the expected fraction of VTs that are killed, *KVTP*. When three engagements are allocated, it is quite low—less than 0.5 (*KVTP*)—but recall that the maximum probability that can be achieved with three engagements is 0.6, since there are five sites. In allocating four engagements, the planner takes a higher risk that the mission will take longer than the available time, *E*, but the probability of success becomes higher than 0.6. For both cases (three or four engagements), it is clear that the choice of firing policy does not make much difference with respect to *KVTP*—the results are similar for high and low values of γ. Notice for the cases studied, that the high firing threshold (higher γ) increases the expected mission time (*EMT*) without a significant increase in the performance (*KVTP*); however, a longer expected mission time may result in a higher probability the target will successfully hide. Since the expected mission time for a cautious firing policy will tend to be smaller, the probability the VT will successfully hide will be smaller. There is no shortage in ammunition—less than two munitions are expected to be expended (*MEP<0.5*), and all three engagements are likely to be executed in the mission (high *EPP*). Assuming that the planner is willing to take the higher risk of not completing the mission on time, the nominal mission plan is to allocate four munitions and four engagements, set the classification window at one minute, and use cautious firing policy.

Without any classification process, assuming that the operator shoots at one object at each engaged site, there is a probability of 0.8 to attack the launcher (there are 4 munitions, thus 4 possible attacks on five sites). The weapon's single shot kill probability is 0.8. Thus there is a probability of 0.64 to kill the launcher without any classification effort. This result is higher than the *KVTP* in Table 6, a fact, which encourages seeking a better mission plan. The expected mission time of such a plan is only 2.67 minutes. Nevertheless, engagement with classifications may reduce the collateral damage, as fewer of the munitions are expected to be fired. There are operational situations when reducing the collateral damage is important.

3. Achieving Higher KVTP with More Engagements

In order to increase the probability of mission success, the number of engagements *N* should be further increased; with four engagements, the *KVTP* is bounded by the probability of engaging the launcher, 0.8. The increase in *N* can be achieved by shortening the classification window, which would decrease the duration of each engagement. In this case, the benefit of additional engagements may be degraded by reduced classification accuracy due to the effect of time stress on the operator. In order to decide on how much the classification window should be shortened, the planner should decide on a time margin for completing the mission. This time-margin is the difference between the time available for the mission, *E*, and the expected mission time, *EMT*, that is, $E - EMT$. It reflects the risk of not completing the mission on time. Assuming no margin at all, i.e., *EMT* = *E*, the planner tries to set the classification window and firing policy such that the fraction of killed VTs, *KVTP*, is maximized and the expected time of the mission is less than or equal to 3 minutes. The results of such a plan as a function of the number of engagements for Expert operator are shown in Figure 15. In all cases $M=4$, the classification window, T, and the firing threshold are set to maximize the *KVTP* for a given N. Table 7 presents the MOE and the values of the mission parameters (T, N, and γ) for the points of maximum *KVTP*. The smallest number of engagement is obtained when the classification window is unbounded (T is unlimited). The cases where the classification window is unbounded are modeled as if a classification window of twice the reference time, T_{ref}, is perceived for the scaling of the probability function for the decision duration, D. The classification process is not truncated by a decision deadline, so the classification ends when a classification decision is made. Hasty operator can complete 5 engagements for unbounded classification window; thus this is the minimum number of engagements appearing for him in Figure 15.

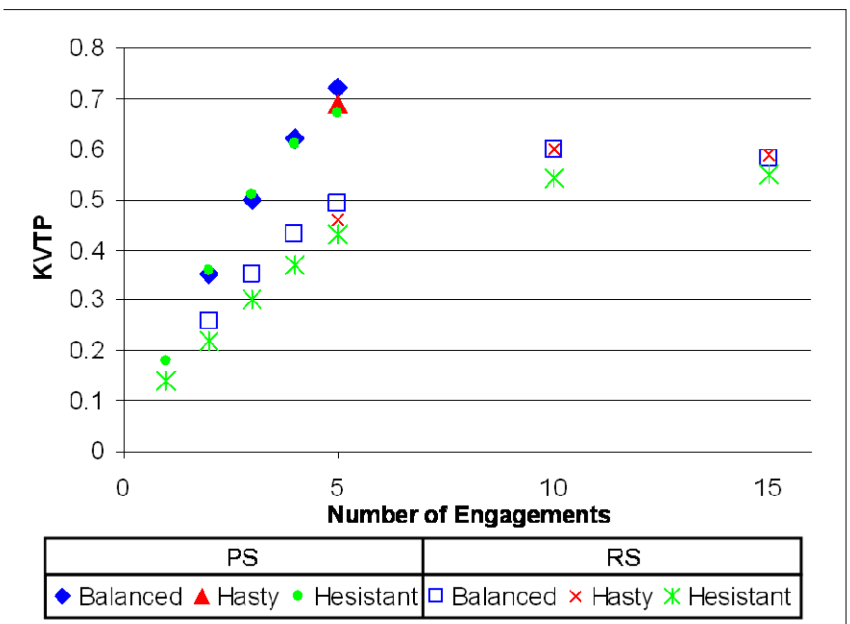

Figure 15. Expected Fraction of VTs Killed vs. the Number of Engagements in Scenario A.

The maximum probability of killing the VT (*KVTP*) of PS, with any type of operator (see Table 7), is higher than this probability when there are four engagements without classification, 0.64 (see Table 6). Thus, increasing the number of engagements does seem to be effective with respect to the *KVTP* MOE.

Shooter	Speed	T	N	γ	*KVTP*	*EPP*	*MEP*	*EMT*
PS	Balanced	0.72	5	0	0.72	0.95	0.59	3.00
	Hasty	NA	5	1	0.69	0.93	0.62	2.76
	Hesitant	0.3	5	1	0.67	0.83	0.89	3.00
RS	Balanced	0.23	10	NA	0.60	0.43	0.88	2.99
	Hasty	0.78	10	NA	0.60	0.45	0.87	3.00
	Hesitant	0.14	10	NA	0.55	0.35	0.91	3.00

Table 7. MOEs and Mission Parameters for Maximum *KVTP*.
KVTP—fraction of VTs killed, *EPP*—fraction of engagements performed, *MEP*—fraction of munitions expended, *EMT*—expected mission time (minutes).
Unlimited classification window for Hasty PS assumes that the operator perceives a classification window of twice the reference time (2min), though the classification window is not truncated after 2min.
RS uses neutral firing policy and does not follow a γ-firing policy.

For both the Persistent and Random shooters, increasing the number of engagements and shortening the classification window increases the *KVTP*. The Random shooter, who is Balanced or Hasty reaches his maximum *KVTP* at 10 engagements (in this case T is very short, see Table 7). Further increase of the number of engagements, by shortening the classification window even more, results in inferior *KVTP*. This maximum represents a balance between speed and accuracy. In this scenario, where the density of VTs is very low, speed is more important than accuracy. This fact is the reason for the higher maximum performance of a Hasty RS over a Hesitant RS. Notice that the Random shooters are expected to execute less than half of their engagements due to munitions shortage (*EPP<0.5* in Table 7).

The Balanced PS reaches his maximum *KVTP* when the firing policy is set to cautious ($\gamma = 0$). Using this policy, allows more time to be spent on classification rather than shooting (recall that each shot requires $\mu_F = 30\sec$, on average). It also makes it less likely that the operator will shoot at WTs and therefore reduces collateral damage and waste of munitions. This result is different than the results presented in Table 6. For the result displayed in Table 6, greedy firing policy is maximizing the *KVTP* as the classification window is not adjusted to maximize the usage of the time available for the mission (3 minutes), and there is enough time for shooting more at each attack. Since the scenario is munitions-rich (there are many munitions compared with the number of targets and the time to shoot them, see low *MEP* values in Table 6), shooting more only contributes to the *KVTP*, as no early termination of the mission due to munitions shortage will occur. The Hesitant PS maximizes his *KVTP* when the firing policy is set to greedy ($\gamma = 1$). Since the Hesitant operator tends not to decide, and there are enough munitions, greedy firing policy guarantees more shots (higher *MEP* in Table 7). However, in this case, less time can be spent on classification. The balance of speed and accuracy causes the maximum *KVTP*. of the Hesitant PS to be inferior compared with the Balanced PS.

We also notice that the maximum probability of killing the launcher by the Persistent shooter is about 0.7, only 17% higher than the Random shooter, whose probability of killing the VT is about 0.6. In a munitions-rich, low VT density scenario, we don't observe a very large advantage of the Persistent shooter over the Random shooter. This is quite surprising due to the clear operational advantage of Persistent shooting tactics. However, the Random shooters shoot much more (see higher *MEP* in Table 7) than the Persistent shooters, which results in more collateral damage.

Based on the results above, the planner should decide on a robust mission plan, not knowing if stress will be experienced by the operator and will cause him to be Hasty or Hesitant. Although operators of all three types can achieve similar *KVTP* in a given scenario, this performance is achieved under *different* mission plans, with different firing policies and classification windows (see Table 7). If operator’s stress is significant, then no one mission plan can guarantee higher *KVTP* over the nominal plan, the outcomes of which are displayed in Table 6 (*M=4, T=1, N=4,* $\gamma = 0$), or over a mission with engagements without classification at all (*KVTP=0.64*).

A compromise, which yields small improvement (about 10%) over the nominal plan for Balanced operator is to allocate *N=5* engagements with a classification window of *T=27* seconds and use the greedy policy ($\gamma = 1$). This policy maintains the KVTP value of the nominal plan if stress makes the operator Hesitant, and degrades it (about 18%), if the operator turns Hasty. The expected time to complete 4 engagements for a Hesitant operator is approximately 3 minutes. The performance in this case for Expert operator is presented in Table 8.

Speed	N	γ	*KVTP*	*EPP*	*MEP*	*EMT*
Balanced	5	1	0.66	0.91	0.70	2.57
Hasty	5	1	0.51	0.91	0.71	1.81
Hesitant	4	1	0.61	0.89	0.79	2.98

Table 8. MOEs for Scenario A with *T=27sec*.
KVTP—fraction of VTs killed, *EPP*—fraction of engagements performed, *MEP*—fraction of munitions expended, *EMT*—expected mission time (minutes).

4. Achieving Higher KVTP with Technological Improvements

When the engagements do not include a classification process, each engagement is shorter and therefore we can assume that there will be always enough time to shoot all $M = 4$ munitions. Since there are $K = 5$ possible target sites, the probability of killing the launcher, if each site is attacked with one munition is $0.8p$. We assume that increasing the number of munitions is not possible due to design constraints of the UCAV.

Seeking to improve the performance in this scenario, two technological improvements are suggested:

1. **Improved Electro-optical Payload (IEP):** operators will have higher q_∞. Expert operators will have $q_\infty = 0.97$.
2. **Improved Lethality Munitions (ILM):** munitions have higher kill probability and more noticeable effect on the target. With the new weapon, the probability of kill is $p = 0.95$ and the probability that there is a clear evidence of a kill is $b = 0.95$. The additional weight of this weapon will reduce the capability of the UCAV to carrying only two munitions of this type.

With the heavier munitions, the UCAV shoots less. Thus, more time is available for classification, and the classification window can be longer than 27 seconds. Adjusting the expected mission time to be similar to that of a Balanced operator in the previous mission plan (*M=4, T=27 seconds,* $\gamma=1$*,N=5*, see Table 8), a classification window of 40 seconds was chosen. The mission performance of Expert operators, given the improvements, is displayed in Table 9.

Modification	Speed	γ	*KVTP*	*EPP*	*MEP*	*EMT*
None	Balanced	1	0.66	0.91	0.70	2.57
	Hasty	1	0.51	0.91	0.71	1.81
	Hesitant	1	0.61	0.89	0.79	2.98
IEP	Balanced	0	0.69	0.94	0.60	2.35
		1	0.70	0.91	0.69	2.53
	Hasty	NA	0.53	0.91	0.70	1.79
	Hesitant	0	0.36	0.98	0.29	1.95
		0.5	0.45	0.98	0.44	2.25
		1	0.63	0.89	0.77	2.95
ILM	Balanced	0	0.65	0.82	0.77	2.57
		1	0.63	0.75	0.84	2.65
	Hasty	1	0.46	0.75	0.85	1.50
	Hesitant	0	0.36	0.95	0.40	2.50
		0.5	0.43	0.95	0.59	2.72
		1	0.53	0.71	0.92	3.11
IEP+ILM	Balanced	0	0.71	0.84	0.74	2.54
		1	0.69	0.77	0.82	2.63
	Hasty	1	0.48	0.76	0.84	1.49
	Hesitant	0	0.38	0.95	0.37	2.46
		0.5	0.47	0.95	0.57	2.69
		1	0.56	0.72	0.91	3.10

Table 9. MOEs for Scenario A with Technological Improvements. *KVTP*—fraction of VTs killed, *EPP*—fraction of engagements performed, *MEP*—fraction of munitions expended, *EMT*—expected mission time (minutes). ILM is implemented with classification window of 40 seconds. In all other cases the classification window is of 27 seconds.

ILM degrades the performance as there are fewer munitions, and the mission is more likely to terminate before all the engagements are performed due to munitions shortage (lower *EPP*). Thus, munitions with increased performance, but higher weight do not improve the *KVTP*. They do enable a longer classification window, and therefore may reduce the effect of time stress. Therefore, it may reduce also the chance for a change in operator’s behavior, and thus maintain the Balanced operator's performance.

IEP slightly increases the *KVTP* (compare with Table 8) of the operators. Operators under stress, however, are not much benefited from the improved payload. Hasty operator (increase of 4% in the *KVTP*) decides too fast, before the payload contributes much. The Hesitant operator (increase of 3%) does not decide a lot, so the improved performance of decisions does not contribute much. Additional contribution may be in less stress, as the mission becomes easier with the improved sensor.

The combination of IEP and ILM does not seem to improve much the *KVTP* compared with the situation where only IEP is implemented. It actually degrades the *KVTP* of Hasty and Hesitant operators (Table 9). However, the combination may reduce the effect of time stress and therefore may avoid Hasty and Hesitant behaviors. In any case, the suggested technological improvements, which enhance the classification and shooting capabilities, do not significantly increase the performance of the HK with respect to the *KVTP* (3%-6% for the cases of maximum increase in *KVTP*. Compare Table 9 and Table 8). The reason is lack of time.

Another result is that unlike the munitions-rich scenario, when having only two munitions available, cautious rather than greedy firing policy maximizes the *KVTP* of Balanced operator (compare with the baseline plan results in Table 6). This is due to early termination of the mission because of munitions shortage (*EPP=0.75*). However, for Hesitant operators, the greedy policy is still preferable in this scenario (KVTP of 0.56 with $\gamma = 1$ and only 0.38 with $\gamma = 0$).

C. SCENARIO B: AMBUSHING SAM BATTERIES

1. Operational Setting

Synthetic Aperture Radar (SAR) imagery revealed a possible hostile mobile surface-to-air (SAM) battery in ambush along a planned intrusion route for a deep strike mission. The deep strike is scheduled within one hour. It is assumed that due to the high concealment under vegetation and radio silence, the hostile SAM battery will not move until the attack. It is known that the enemy's SAM batteries consist of six TELAR (see glossary) vehicles. Nevertheless, the image revealed eight suspect vehicles deployed. Figure 16 presents a schematic illustration of this scenario.

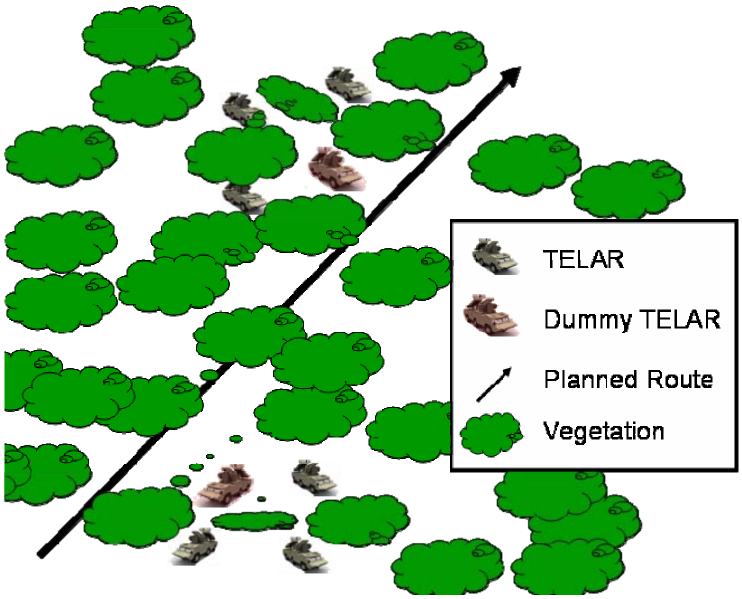

Figure 16. Schematic illustration of scenario B theater.
Each TELAR marks a site for classification. Dummy TELER is in Reddish Shade.

A UCAV loitering above the area is sent to clear the route before the attack. The time allocated for this mission is 45 minutes. The UCAV is carrying only four munitions, and due to operational constrains, only one replacement, with another UCAV carrying another load of four munitions, can be carried out before the strike operation begins. Hence, there are only eight munitions available for the mission.

Table 10 presents the parameter for this mission.

E	K	K_{VT}	μ_C	T_{Ref}	q_∞	μ_P	μ_F	p	b
45	8	6	4	2	0.9	0.3	0.3	0.8	0.8

Table 10. Nominal Parameters for scenario B.
μ_C—expected time between engagements (see Section C in Chapter IV), μ_P—expected duration of preceding preparations for an attack (see Section D in Chapter III), μ_F—expected duration of each shot (see Section D in Chapter III), T_{ref}—reference classification window for normal operational conditions (see Section C in Chapter II), q_∞—the limiting probability of correct classification for Expert operator (see Section C in Chapter II), p—the single shot kill probability, b—the probability that a target emits signs of being killed following a kill.

2. Baseline Mission Plan

Assume that the operator is Balanced Expert and using Persistent shooting tactic. The mission planner first allocates all the available munitions, $M=8$. When using the reference time for the classification window, $T = T_{ref} = 2min$, the number of engagements that can be performed before the *EMT* exceeds *E*, is exactly eight, which means that all the sites can be engaged by a Persistent shooter. The performance in this case is presented in Table 11.

γ \ MOE	*KVTP*	*EPP*	*MEP*	*EMT*
0	0.74	0.96	0.85	43.75
1	0.75	0.95	0.88	43.86

Table 11. MOEs for Scenario B with $T=2min$.
KVTP—fraction of VTs killed, *EPP*—fraction of engagements performed, *MEP*—fraction of munitions expended, *EMT*—expected mission time (minutes).
$N=8$ engagements.

We see a balanced plan, in which many of the munitions are fired (high *MEP*), the engagements are almost fully exhausted (high *EPP*), and it yields reasonably good expected results of killing 75% of the VTs (*KVTP*). The expected time of the mission, however, is quite close to the deadline of 45 minutes (*EMT*), which is undesirable.

Engagements with no classifications, in which the eight sites are attacked with one munition each, yields *KVTP* of 0.8, as all the VTs are engaged, and each is killed with probability 0.8. This performance is better than the performance displayed in Table 11 (with a price of firing more munitions, and causing more collateral damage). The expected mission time of such a tactic is 36.80 minutes.

3. When More Munitions Are Available

In the case above a lot of the munitions are expended ($MEP=0.88$). This observation suggests that additional munitions may improve the performance, and increase the *KVTP*. Suppose that another UCAV replacement is possible, so the number of munitions, available and allocated, is increases by 50% to 12.

Table 12 indicates that there is some improvement in the *KVTP* (0.81 vs. 0.75) for more munitions (8%), as most of them are not in use, as there is a reduction in the fraction of munitions expended (*MEP*). The UCAV with the additional munitions is expected to kill 80% of the VTs—as good as in the case of engagements without any classification. The time restriction becomes even more problematic. A few long engagements may easily cause a failure to complete the mission on time.

M	γ	*KVTP*	*EPP*	*MEP*	*EMT*
8	1	0.75	0.95	0.88	43.86
12	1	0.81	1.00	0.68	44.28

Table 12. MOEs for Scenario B with eight and 12 munitions. *KVTP*—fraction of VTs killed, *EPP*—fraction of engagements performed, *MEP*—fraction of munitions expended, *EMT*—expected mission time (minutes). $N=8$ engagements. $T=2$ minutes.

In order to cope with the time restriction, the planner may reduce the number of engagements by one, or shorten the classification window. Table 13 displays the mission performance for combinations of shorter classification window and one fewer engagement with and without additional ammunition. The classification window is reduced to 7/8 of its original length—the same ratio of the reduction in the number of engagements. We assume that this minor reduction in the classification window will not induce effective stress on the operator. Clearly, no much reduction in the mission time is achieved by these techniques, as the changes are quite minor—about one minute is shaved from the expected mission time. The *KVTP* is not much degraded as well. Short classification window with additional munitions and cautious firing policy (plan 7 in Table 13) can maintain half of the improvement in *KVTP* gained by the additional munitions, and keep a margin of 2 minutes from the mission deadline. Thus, this is the preferable mission plan.

4. When Time Is Not a Significant Constraint

Suppose now that the strike mission can be delayed, and the UCAV can get much more time for the mission. Previously the time was adequate for exactly eight engagements. Additional time allows longer classifications, and more shootings. The planner thus does not pose any classification window. We assume that in such a case, a classification window of twice the reference time, T_{ref}, is perceived as infinite for the scaling of the decision duration function. Thus, the operators will perceive the unlimited classification time as if they have four minutes to decide. In this case, the operators almost reach their performance limits. The infinite Classification Window is modeled by using a classification window ten times larger than the perceived infinite classification time, i.e., 40 minutes long. This is practically infinite for computing the probabilities, as the area under the tail of the density function of the decision time is negligible.

Plan	*M*	*T*	*N*	γ	*KVTP*	*EPP*	*MEP*	*EMT*
Reference	8	2	8	0	0.74	0.96	0.85	43.75
				1	0.75	0.95	0.88	43.86
1	8	2	7	0	0.66	0.98	0.78	42.59
2				1	0.68	0.97	0.81	42.72
3	12	2	7	0	0.69	1.00	0.58	42.81
4				1	0.72	1.00	0.61	42.99
5	8	1.75	8	0	0.73	0.96	0.85	42.69
6				1	0.73	0.95	0.87	42.80
7	12	1.75	8	0	0.78	1.00	0.65	43.03
8				1	0.80	1.00	0.68	43.21

Table 13. MOEs for Scenario B with Shorter Mission Time.
KVTP—fraction of VTs killed, *EPP*—fraction of engagements performed, *MEP*—fraction of munitions expended, *EMT*—expected mission time (minutes).
Reference case refers to Table 11. Operator is Expert PS.

Table 14 presents the MOEs values, the expected time spent on classification, and the standard error of the time spent on classification for different classification windows.

Notice that when greedy firing policy is used, Hesitant operator always performs better in terms of *KVTP* than the other operators. The reason can be understood intuitively as follows: When there is a finite classification window, the Hesitant operator does not make many decisions, and fires when he doesn't make a decision. When he does make a decision, the decision is usually accurate—fire at a VT. Hesitant operator gets to fire more (higher *MEP*) than the Balanced and the Hasty operators. Since there are many munitions, and the density of VTs is very high, he attacks more VTs. When the classification window is unbounded, Hesitant will take his time, and when he decides, he decided more accurately than operators with other speed of performance. An almost abnormality of this situation can be seen when the classification window is finite. The Hesitant operator will be as accurate as his skill level allows when making a decision.

However, there will be cases where he makes no decisions. In these cases, he attacks due to the greedy firing policy. Thus, he attacks more in the case where the classification window is bounded than in the case where the classification window is unbounded. Because of the high density of VTs, and availability of munitions, when he shoots without a decision he is likely to kill a VT, and the performance in terms of *KVTP* is better when the finite window is applied than in the unbounded classification window case. As the window gets longer, the decisions of the Hesitant operator become better, and thus the overall performance gets better up to a point when the classification decisions are as accurate as possible. Lengthening further the classification window at this point will reduce the number of shots without improving much the quality of the decisions, resulting in inferior overall performance.

T	Speed	Mean	Std	γ	*KVTP*	*EPP*	*MEP*	*EMT*
1.75 min	Balanced	7.16	1.20	1	0.80	1.00	0.68	43.21
	Hasty	2.10	0.35	NA	0.63	1.00	0.57	37.53
	Hesitant	11.20	1.20	1	0.89	0.99	0.80	48.00
2 min	Balanced	8.18	1.37	1	0.81	1.00	0.68	44.28
	Hasty	2.40	0.40	NA	0.64	1.00	0.58	37.87
	Hesitant	12.80	1.37	1	0.90	0.99	0.80	49.61
Unbounded	Balanced	16.80	3.17	1	0.86	1.00	0.68	52.92
	Hasty	4.80	0.81	NA	0.73	1.00	0.62	40.53
	Hesitant	32.80	6.33	1	0.88	1.00	0.69	68.97
4 min	Balanced	16.36	2.73	1	0.87	1.00	0.71	52.61
	Hasty	4.80	0.81	NA	0.73	1.00	0.62	40.53
	Hesitant	25.60	2.74	1	0.92	0.99	0.81	62.46

Table 14. MOEs for Scenario B with Different Classification Windows.
Mean refers to mean time spent on classifying targets in the mission. Std stands for standard deviation of time spent on classifying. *KVTP*—fraction of VTs killed, *EPP*—fraction of engagements performed, *MEP*—fraction of munitions expended, *EMT*—expected mission time (minutes).
There are eight targets, six of which are VTs and 12 Munitions available.

For Hesitant operator and for Balanced operator, when the classification window is long enough, the *KVTP* is higher than the case of engagements without classification (0.8). Thus, when the time is not a significant constraint, the classification contributes to the mission success.

Another result worth noticing is that even when the time is not a constraint, applying a long finite classification window does not degrade the *KVTP* (in this specific scenario it even improves it), and significantly decreases the variability of the classification time of Balanced and Hesitant operators. When time is a constraint, this control of variability helps make sure that the mission will end on time.

5. When Resources Become Scarce

Assume now that the attack is suddenly expedited, and only 35 minutes are available for the UCAV mission. In addition, the UCAV carries only four munitions, and there is no other available UCAV to reinforce. Thus the mission planner allocates only $M=4$ munitions for the mission. In this case the mission becomes resource-scarce.

As the time is really tight, the planner should choose if the mission will consist of short classification windows and many engagements or of longer classification windows and fewer engagements. Assume that the planner knows the skills and speed of the operator involved in the mission, and can adjust the classification window such that the expected mission time will be 35 minutes.

Figure 17 displays the mission performance in term of *KVTP* for different mission plans for different types of operators; the mission performance for the Random shooter is displayed for reference. Greedy firing policy is used for all, as it turns out to be the best according to our model (due to the high density of VTs and low number of WTs).

For engagements without classification process, there is a probability 0.21 that all four engagements will engage a VT, a probability 0.57 that three VTs will be engaged, and a probability 0.21 that only two VTs will be engaged. The *KVTP* for this mission plan is 0.4. Lower than the case with classification. The expected mission time is 18.40 minutes. When the munitions are a scarce resource, the classifications contribute to the mission performance.

When the classification Window is unbounded, a Hesitant operator can have four engagements, Hasty operator can have seven engagements and Balanced operator can have five engagements. A Persistent shooter achieves higher performance than that of a random shooter. Nevertheless, the behavior of the *KVTP* as a function of the number of engagements is similar for the two shooting tactics. Trying to engage all the sites degrades the mission performance. For Balanced PS, six engagements maximizes the performance. For Hesitant or Hasty operators, seven engagements maximizes the performance.

When trying to engage all the targets (*N=8*), Hesitant PS performs better than Balanced or Hasty operators in terms of *KVTP*. When the classification window is very short, the decisions of the operators are not very good. In a scenario with high VT density, even when munitions are in shortage, it is better to shoot than to classify if the classification quality is not high enough. A Hesitant operator shoots more than the other operators in this case, when the greedy firing policy is used.

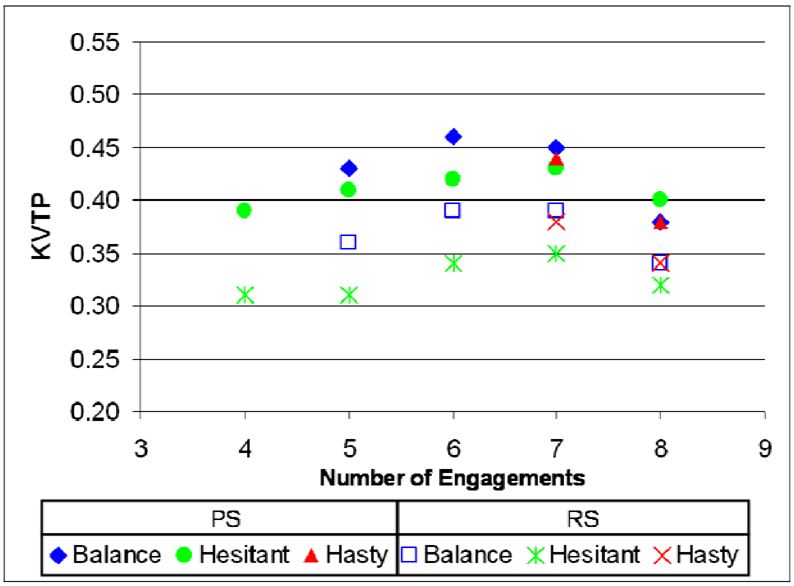

Figure 17. Expected Fraction of Killed VTs vs. the Number of Engagements.

Notice that unlike the resource-rich case (Table 14), here, Hasty operator has higher maximum performance than Hesitant operator. In a resource-scarce scenario with high density of VTs, it turns that it is better to trade accuracy for speed. Notice, however, that the difference in the maximum performance of the different types of operators is relatively minor.

6. When Density Decreases

Assume now that intelligence report arrived just before the UCAV is sent, informing that the deployed SAM battery is likely to miss two TELARs which are found in a workshop due to technical failures. The mission planner concludes that there are only four VTs among the eight objects.

Again the planner is interested in setting a classification window and a firing policy. Consider first the resource-rich case. Assume that, again, the time constraint may be removed, and up to 12 munitions can be fired in the mission. The mission now is resource-rich. Table 15 presents the performance under different classification windows. Table 16 presents the relative change in the MOE values compared with the high VT density scenario (see Table 14).

Classification window	Speed	Mean	Std	γ	*KVTP*	*EPP*	*MEP*	*EMT*
1.75 min	Balanced	7.14	1.20	1.00	0.81	1.00	0.56	42.42
	Hasty	2.08	0.35	NA	0.63	1.00	0.51	37.15
	Hesitant	11.18	1.19	1	0.90	0.99	0.71	47.21
2 min	Balanced	8.16	1.36	1	0.82	1.00	0.56	43.44
	Hasty	2.40	0.41	NA	0.65	1.00	0.51	37.45
	Hesitant	12.82	1.37	1	0.91	0.99	0.71	48.77
Unbounded	Balanced	16.80	3.17	1	0.87	1.00	0.52	51.89
	Hasty	4.80	0.82	NA	0.73	1.00	0.52	39.87
	Hesitant	32.80	6.33	1	0.89	1.00	0.51	67.86
4 min	Balanced	16.38	2.73	1	0.87	1.00	0.56	51.53
	Hasty	4.80	0.82	NA	0.73	1.00	0.52	39.87
	Hesitant	25.58	2.74	1	0.93	0.99	0.71	61.25

Table 15. MOEs for Scenario B with Different Classification Windows, Mediocre VT Density.

Mean refers to mean time spent on classifying targets in the mission. Std stands for standard deviation of time spent on classifying. *KVTP*—fraction of VTs killed, *EPP*—fraction of engagements performed, *MEP*—fraction of munitions expended, *EMT*—expected mission time (minutes).

There are eight targets, six of which are VTs and 12 Munitions available.

There is almost no change in the classification duration or in *KVTP*. Since there are fewer VTs, the operators shoot less (*MEP*); this is particularly true for the Balance operator, whose decisions are influenced more by the scenario. This is because the Balanced operator is making fewer mistakes than Hasty operator and more decisions than Hesitant operator.

Assume again that the strike is expedited. The scenario has now less resources. Recall that in scenario A (Section B above), when the scenario was limited in resources and had very low VT density, the firing policy that yielded better results (higher *KVTP*, see Table 7) was not greedy. Figure 18 presents the *KVTP* as a function of the number of engagements for each operator with adjusted classification windows.

Notice that the expected performance in terms of *KVTP* is higher for the lower density case for all operators (compared with Figure 17). That is due to the fact that there are more munitions per VT, allowing the UCAV to kill more of the VTs. An interesting result is that in this scenario, similar to scenario A with the low VT density, Balanced operator maximizes his *KVTP* with cautious firing policy. The Hesitant operator still performs better with the greedy firing policy. Another interesting result is the shift of maximum *KVTP* of Hesitant operator to six engagements. When the density of VTs is lower, it is more important for the Hesitant operator to be more accurate, rather than being able to shoot at one more target. There is not enough time for shooting more, as the gain in terms of killed VTs from shooting at one more target is lower in a less dense scenario.

Classification window	Speed	Mean	Std	γ	*KVTP*	*EPP*	*MEP*	*EMT*
1.75 min	Balanced	0%	0%	1	1%	0%	-18%	-2%
	Hasty	0%	0%	NA	0%	0%	-11%	-1%
	Hesitant	0%	0%	1	1%	0%	-11%	-2%
2 min	Balanced	0%	0%	1	1%	0%	-18%	-2%
	Hasty	0%	1%	NA	2%	0%	-12%	-1%
	Hesitant	0%	0%	1	1%	0%	-11%	-2%
Unbounded	Balanced	0%	0%	1	1%	0%	-24%	-2%
	Hasty	0%	1%	NA	0%	0%	-16%	-2%
	Hesitant	0%	0%	1	1%	0%	-26%	-2%
4 min	Balanced	0%	0%	1	0%	0%	-21%	-2%
	Hasty	0%	1%	NA	0%	0%	-16%	-2%
	Hesitant	0%	0%	1	1%	0%	-12%	-2%

Table 16. Change in MOEs for Scenario B with Lower VT Density.
Mean refers to mean time spent on classifying targets in the mission. Std stands for standard deviation of time spent on classifying. *KVTP*—fraction of VTs killed, *EPP*—fraction of engagements performed, *MEP*—fraction of munitions expended, *EMT*—expected mission time (minutes).
Reference values are shown in Table 14.

In this case, as well, Hasty operator performs slightly better than the Hesitant operator. We may conclude that when time is very scarce, it is worthwhile to trade accuracy with speed even when the density of VTs is not very high (50% in this scenario). This is in agreement with scenario A iin the previous Section, where the density of VTs is very low (20%).

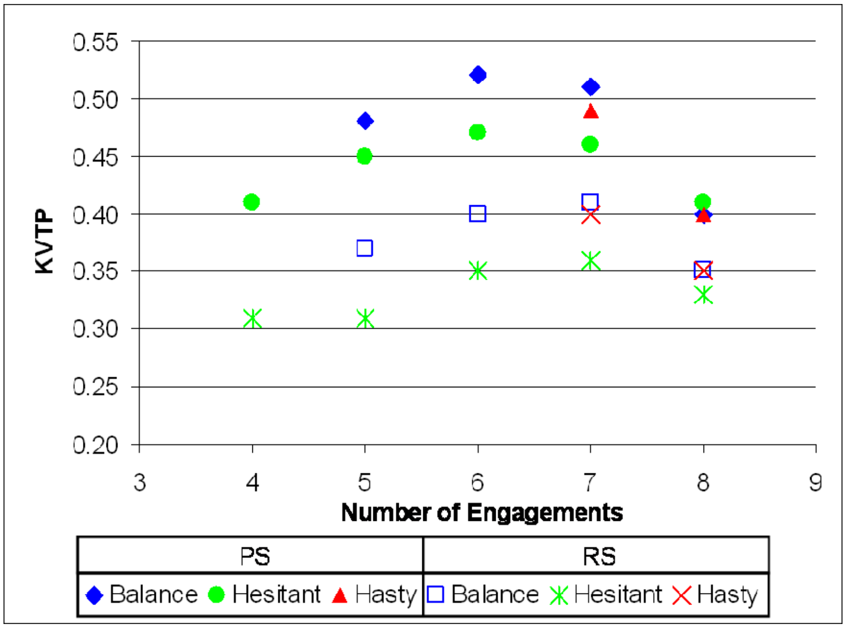

Figure 18. Expected Fraction of VTs Killed vs. the Number of Engagements.

VI. SUMMARY AND CONCLUSIONS

In this chapter, we highlight the modeling contributions in this thesis and discuss some important operational insights regarding Hunter-Killer missions using persistent shooting tactic.

A. MODELING CONTRIBUTION

In this thesis we extend previous research on stand-off precision fire to account for human factors and decision making in an integrated fire engagement model. The suggested model covers two phases in the mission of a hunter-killer: the planning phase and the execution phase. The planning phase allows a mission planner to set decision variables, which control the way the HK executes the mission in order to maximize his expected performance subject to operational constraints. In the execution phase the HK engages target sites, where each engagement comprises a target acquisition (classification) process, which may lead to a shooting process according to the shooting policy. The shooting process is governed by parameters that can be dynamically updated during the mission.

The effect of time on the mission performance is manifested in two interrelated challenges. First, the duration of the mission is constrained by operational considerations. Therefore, the challenge at the *mission* level is to balance between the number of engagements that can be fit into the mission time frame and the effectiveness of a single engagement. Longer engagements are more effective but fewer of them can be executed in a given time window. At the *engagement* level time stress affects the capabilities and performance of the operator and the challenge is to determine the classification window due gives the best “bang (kill rate) for bucks (time)”.

Data from field experiments and operational activity can be collected to estimate model parameters; in this way aspects of real-world operations may be examined.

B. THE EFFECT OF SCENARIO CHARACTERISTICS ON THE MISSION PARAMETERS

A scenario is characterized by the number of target sites, number of valuable targets and the signature, vulnerability and time sensitivity of these targets. These characteristics affect the resources needed to engage the targets and the tactic that is used. The scarcest resource in time-sensitive scenarios is *time*; the mission must be completed within a short period of time. In other scenarios the supply of munitions may be the critical component in the mission plan, when operational and logistical constraints limit the supply of munitions. Scenarios with low density of valuable targets or where targets are well concealed or camouflaged affect the effectiveness and efficiency of the mission because the targets are difficult to acquire.

The operational scenarios, which are explored in Chapter V, differ in the availability of mission resources, in the density of valuable targets, and in the number of sites involved. The Available *time*, affects the number of engagements that are assigned to the HK, the length of the classification window and the firing policy chosen. The amount of *munitions* and the *number* of VTs, (relative to the number of sites) influence the firing policy and the balance between accuracy and speed in the mission plan.

C. EFFECTS OF THE CLASSIFICATION WINDOW

The classification window has three effects on the mission. First, it limits the accuracy of the classification. Second, it may cause time stress that changes the operator's behavior, such that his speed of performance is changed, and third, shorter classification window facilitates more engagements in the limited time allocated for the mission.

In scarce-resource scenarios (both time and ammunition), when the density of VTs is at least 50% (scenario B in Chapter V), a balance between the classification accuracy and speed, that is a balance between the number of engagements and the length of the classification window, can maximize the performance in the mission. This observation, and the fact that time stress may reduce the effectiveness of the classification process (see Chapter V where the Balanced operator achieves higher mission performance in all the scenarios), imply that longer classification windows are more desirable, even though the number of possible engagements may be reduced.

D. EFFECTS OF FIRING POLICY

The firing policy affects the mission performance in three aspects. First, greedier firing policy (i.e., larger value of γ) makes the shooter (especially the Hesitant shooter) attack more often, and thus in resource-rich scenarios—both ammunition and time—it increases the expected number of VTs killed. Second, attacking more often reduces the munitions efficiency because more WTs are attacked and fewer munitions are available for attacking the VTs. In resource-scarce scenarios, inefficient consumption of munitions degrades the *KVTP*, due to early mission termination, caused by munitions shortage. Third, attacking more often increases the time spent on shooting in the mission. Therefore there is less time available for classification, which may induce shorter classification windows, with their consequences—possible stress, and degraded classification accuracy.

We observe a need to balance and adjust the firing policy according to the density of VTs in the scenario, the availability of resources and the type of the operator. Hesitant operator should use, in general, greedy firing policy in all the cases that were examined in our analysis. Balanced operator should use cautious firing policy in resource-scarce scenarios, and greedy firing policies in others.

E. EFFECTIVE MISSION PLAN

The conflicting effects of the decision parameters, and their dependency on the operational scenario, demand a careful planning procedure to achieve a robust and effective mission plan.

We showed that the operational effectiveness of Hunter-Killers can be significantly increased by an appropriate allocation of time and munitions for the mission, and by carefully controling the tactical parameters such as the classification window and the firing policy. Robust mission planning should take into account uncertainties in the operator's performance, and avoid point optimization.

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